Rural Poverty in Indonesia:
Proxy-means Tests, Dynamics, and Linkages with Deforestation

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"If we had believed that poverty is unacceptable to us, and that it should not belong to a civilized society, we would have created appropriate institutions and policies to create a poverty-free world"

Muhammad Yunus, *Founder of the Grameen Bank*

Summary

Poverty reduction is one of the major goals of development policies. But besides improvement in living standards that can be realized through reduction of poverty, poverty alleviation can also have positive consequences for natural resources. One such environmental effect that can be achieved through reduction of poverty is the stabilization of rainforest margins in the tropics where poverty is also widespread. Similar to other rainforest regions, the link between poverty and ongoing deforestation is of great policy relevance to the Indonesian government.

This thesis aims at analyzing three aspects of rural poverty in Central Sulawesi, Indonesia:

1. To assess the robustness of two operational poverty assessment models developed in 2005 for Central Sulawesi
2. To gain a better understanding of the poverty dynamics of the region
3. To analyze the connections between poverty and deforestation in the research area

The study contributes to the discussion on the rationale for operational poverty assessment by proxy-means tests. It is also the most recent contributions to the analysis of poverty dynamics in the Indonesian context. Furthermore, the study explores the link between rural poverty and deforestation at the household level.

The study is built on primary data obtained from household surveys in the vicinity of the Lore Lindu National Park in Central Sulawesi. In order to assess the robustness of poverty assessment tools as well as for the analysis of poverty dynamics, two rounds of household surveys were conducted. The first round of survey targeting 264 households was done in 2005 to obtain indicators of poverty and to derive the daily per capita consumption expenditures. In 2007, the same households were again surveyed using identical questionnaires. For both, to evaluate the robustness of the operational poverty assessment tools, and to analyze poverty dynamics in the region, the study uses an absolute definition of poverty based on the two international poverty lines of 1 and 2 US$, and a national poverty line for rural areas. To explore the link between poverty and deforestation, a panel data consisting of three waves of household surveys on income conducted between 2000 and 2006 is used. The dataset contains information on 266 randomly selected households from 12 villages in the vicinity of Lore Lindu

National Park in Central Sulawesi, Indonesia. The analysis of the link between poverty and deforestation uses a relative poverty index that ranks households according to their wealth status.

In 2005, two very promising operational poverty assessment models were developed for Central Sulawesi using 15 proxy indicators to predict absolute poverty based on expenditures. In 2007, both models were tested regarding the extent to which these models are robust over time in terms of prediction power and in terms of their indicator composition. In addition, an indicator based poverty assessment tool provided by the U.S. Agency for International Development for Indonesia was evaluated here using the data set from Central Sulawesi. Regarding the robustness of indicator-based poverty assessment by proxy-means tests, the sets of indicators derived in 2005 were still capable of detecting the very poor households (those living on less then 1 Dollar purchaising power paritiesper capita and day) in 2007. However, the models tend to over-predict the very poor. For the assessment of absolute poverty in the research area, we recommend the use of 15 easy to verify indicators (Model 2) in combination with the quantile coefficients of these indicators derived from the one-step procedure (estimated in 2005). This is based on the comparison of accuracy performance of all tools in both years. The accuracy levels of the two models tested remain similar when estimated using the 2007 dataset. However, the indicator composition of the tools changed. The nationally calibrated tool provided by USAID is shown to perform poorly in terms of accuracy when applied to our data set.

To gain a better understanding of the poverty dynamics in the region, different measures of poverty are compared across the survey years. Additionally, transitions into and out of poverty are obtained. In general severe poverty (less the 1 US$ per capita and day) is shown to have decreased. The headcount index for the severely poor declined insignificantly from 19.3 percent in 2005 to 18.2 percent in 2007. However, people in the research area got poorer over the same period since significantly more people are shown to slipped into expenditures below the 2 US$-poverty line. Moreover, the poverty deficit in 2007 is also shown to be greater than the poverty deficit of 2005 irrespective of which poverty line is used. While 49 percent of the very poor households remain very poor in both survey years, 33 percent of them moved out of severe poverty but still had to live on less than 2 US$ PPP per capita and day. Nonetheless there is also movement in the opposite direction. Twenty-three percent of the households in the category of poor (living on less than 2 US$-poverty line) in 2005, became severely poor (less than 1 US$-poverty line) in 2007. To trace the underlying determinants of chronic and transitory poverty, multi-nominal logit regression analyses were applied. Results show that large households are more likely to be chronically and transitorily very poor. They are also shown to have higher probability of being chronically poor. Lack of access to electricity also makes severe chronic and transitory poverty, as well as chronic poverty more probable. Household without access to social capital are similarly more likely to get chronically very poor. Access to credit reduces the probability of becoming chronically very poor and also makes chronic and transient poverty less likely. Household without access to remittances from relatives working away from home are also more prone to (severe) chronic poverty. Finally, lack of opportunities to in engage non-agricultural income generating activities increases the probability to become chronically or transitorily very poor.

Results from the study on the linkage between poverty and deforestation suggests that conversion of forest into farm land in the research area is indeed a severe problem. Approximately 52 km^2 of forest area was converted into farm land between 1999 and 2006 by smallholders. While the poorest and the poor mainly replace forests with subsistence crops such as maize and dry rice, the wealthier households mainly grow cocoa. The findings also show that poorer households are more likely to clear forest than their wealthier counterparts. However, most of the area converted is dedicated to cocoa production. Furthermore, households with younger household heads tend to clear more forest area than households with older household heads. Interestingly, access to social capital tends to increase deforestation. Secure property rights, however, tend to reduce deforestation. Additionally, the location of the household plays a crucial role: households living in a sub-district closer at the forest boarder are more likely to clear forest than those located further away.

In general we find the results quite satisfactory. The study would, however, have benefited from a larger sample size. For example, a more precise calibration of the poverty assessment tools would have been possible if an out-of-sample test was applied. More rounds of expenditure surveys would also allow for use of the components approach to analyze poverty dynamics. Furthermore, the sample used is only representative of the research area and therefore policy implications are hardly applicable to other parts of Indonesia without further analysis of nationally representative data. However, this situation presents a unique advantage since policy implications derived are suited for direct implementation in the research area. With respect to the link between poverty and deforestation, geo-referenced data at plot level would be of great benefit since they could provide more details on the “true” rate of deforestation. However, obtaining such data is often time-consuming and costly.

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List of abbreviations

ADB: Asian Development Bank

BPAC: Balanced Poverty Accuracy Criterion

CBN: Cost of Basic Needs

CIA: Central Intelligence Agency

CIFOR: Center for International Forestry

CGAP: Consultative Group to Assist the Poorest

DCI: Direct Calorie Intake

DFID: Department for International Development

ESCAP: United Nations Economic and Social Commission for Asia and the Pacific

FAO: Food and Agriculture Organization of the United Nations

FEI: Food Energy Intake

FGT: Foster-Greer-Thorbecke

GDP: Gross Domestic Product

Ha: hectare

HDI: Human Development Index

HDR: Human Development Report

IAAE: International Association of Agricultural Economists

IDR: Indonesian Rupiah

IFAD: International Fund for Agriculture Development

IFLS: Indonesian Family Life Survey

IFPRI: Institute for Food Policy Research Institute

IPCC: Intergovernmental Panel on Climate Change

iv: instrumental variable

LLNP: Lore Lindu National Park

LOG: Natural logarithm

LSMS: Living Standard Measurement Survey

MDG: Millennium Development Goal

MFI: Micro Finance Institution

MLE: Maximum Likelihood Estimation

NGO: Non-Governmental Organization

OECD: Organization for Economic Co-operation and Development

OLS: Ordinary Least Squares

p.: page

PA: Participatory Appraisal

PAT: Poverty Assessment Tool

PCA: Principle Component Analysis

PEN: Poverty Environment Network

PES: Payments for Environmental Services

PIE: Poverty Incidence Error

pp.: pages

PPP: Purchasing Power Parity

PRSP: Poverty Reduction Strategy Paper

RA: Rapid Appraisal

REDD: Reducing Emissions from Deforestation and Degradation

RRR: Relative Risk Ratio

Std. Dev.: Standard Deviation

SST: Sen-Shorrocks-Thon

STORMA: Stability Of Rainforest Margins

SUSENAS: Survei Sosial Ekonomi Nasional

TNC: The Nature Conservancy

UN: United Nations

UNDP: United Nations Development Program

US: United States of America

USAID: United States Agency for International Development

Preface

Unfortunately, almost nobody seems to be interested in the question, of why there is poverty in a world so rich in produced goods. By and large people accept that our (global) society produces poverty and try *ex post* to reduce this 'side-effect' of the global economy. Nobody attempts to eliminate poverty (the first Millennium Development Goal of the United Nations to 'eradicate poverty by 2015' only calls for poverty alleviation) and no attempts are made to avoid poverty *ex ante*.

Widespread debate revolves around finding the right strategy for poverty reduction, ranging from calls for re-distribution of wealth to calls for increased economic growth, but seldom the question of whether poverty is a necessary consequence of the existing mode of production is asked.

Regrettably, my study is also limited to contributing to the prevalent views on poverty, dealing with questions regarding the measurement and assessment of poverty, the targeting of poverty reduction programs, the analysis of poverty dynamics, and the environmental consequences (in this case deforestation) associated with poverty.

Nonetheless, I personally believe that it is important to raise the question of whether the current form of economic production and societal organization is capable of both fulfilling people's needs and protecting the environment.

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1. Introduction

The introduction provides a general overview of pertinent background information as well as an outline of the research objectives and the study performed. The case of Indonesia is presented, and underlying theoretical concepts are reviewed.

Each chapter of the thesis focuses on a specific topic and provides a discussion of correspondent theoretical approaches and statistical methods. Chapters 2, 4 and 6 are intended to be self-contained, so some repetitions may occur.

1.1 Problem setting

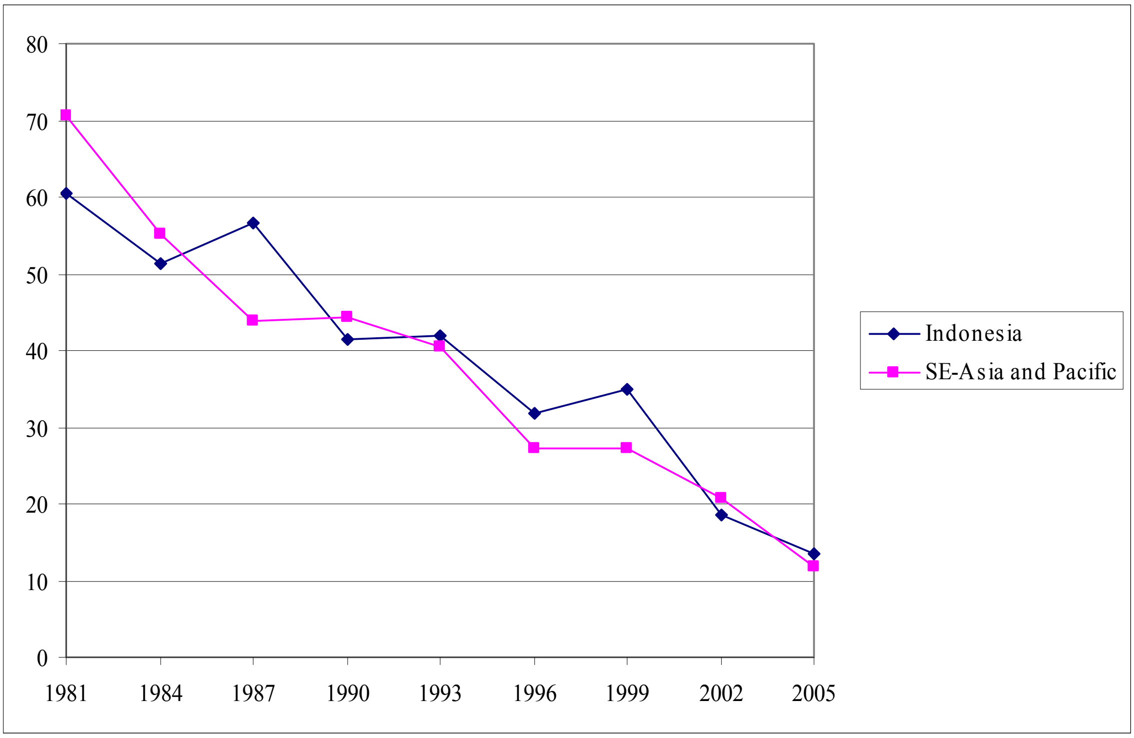
Widespread poverty is one of the most pressing issues of our time. Today it is known that the majority of the world's poor live in rural areas (IFAD 2009). In 2001, 75% of the 1.2 billion people living on less than 1$ US per day, lived in rural areas (IFAD 2001).

Since the early 1990s, more attention has been drawn to combating poverty than ever before. In 2000, the UN Millennium Summit formulated eight Millennium Development Goals (MDG). The first MDG to "eradicate extreme poverty and hunger" calls for halving the number of people living in extreme poverty and those suffering from hunger between 1990 and 2015 (UN 2008).

Between 1990 and 2005 the number of people in developing regions living in extreme poverty (i.e. living on less than 1.25$ per capita per day) declined from 1.8 billion to 1.4 billion. During the same period important headway was made in the effort to eradicate hunger. Today, however, the combination of the economic crisis and rising food prices has had a negative impact on the advances made, and these positive trends will likely to slow or stall completely (UN 2009).

In a regional context – the research presented here was done in Indonesia – the Asian Development Bank (ADB) states an overarching goal of reducing poverty in its borrowing countries (David 2000).

The Asia-Pacific Region is performing quite well economically and is quickly on its way toward achieving the Millennium Development Goals (MDG). South East Asia could be referred to as an 'early achiever' of the first MDG (ESCAP 2007). Figure 1 shows the changes in the international headcount poverty rate for Indonesia compared to that of the South East Asia and Pacific Region. The trend in Indonesia is similar to that of the larger region, although some differences can be noted. For example, the increase in poverty after the 1997 economic crises is more notable in Indonesia than in the larger region.



Source: own calculation with PovCal[1]

Figure 1: Development of 1$ headcount poverty rates between 1981 and 2005 for Indonesia and the South East Asia and Pacific Region

Despite positive development over recent decades, poverty is still a pressing problem in Indonesia and is therefore an important issue on the Indonesian political agenda (CIA 2009).

In addition, global climate change and global losses in biodiversity have become increasingly important issues on the international political agenda (Barroso 2009). Both of these issues are closely related to deforestation, and of great importance in Indonesia.

Worldwide tropical deforestation continuous with an alarming rate of 0.6% per year (FAO 2006). Despite assurance from the FAO (2006) that net losses of forests are slowing due to forest planting, landscape restoration, and natural expansion of forests on abandoned land, the world is still losing forests, and this loss has negative consequences for biodiversity, carbon sequestration, soil fertility, and water quality.

[1] PovCal Software is an online poverty analysis tool provided by the PovCalNet of the World Bank.

In South and South East Asia, 33.3% of the total land area is covered by forests. The annual deforestation rate increased from 0.83% for the period from 1990 to 2000, to 0.98% for the period from 2000 to 2005. This rise stands in stark contrast to the global trend of reduced deforestation (FAO 2006). In Indonesia, deforestation is also a top issue on the political agenda (CIA 2009).

The research presented here embarks both poverty analysis and the relation of poverty to deforestation. This study contributes to the discussion on the usefulness and feasability of operational poverty assessment by proxy-means tests, adds the most recent contribution to the analysis of poverty dynamics in the region of Indonesia, and explores the link between rural poverty and deforestation at the household level.

1.2 Research objectives and outline

The research objectives of the study will be described here in detail, with the three main focal points being: 1) to assess the robustness of two operational poverty assessment models developed in 2005 for Central Sulawesi, 2) to gain a better understanding of the poverty dynamics of the region, focusing on the differences between chronic and transitory poverty, and 3) to analyze the connections between poverty and deforestation in the research area.

In 2005 two very promising operational poverty assessment models were developed for Central Sulawesi using 15 proxy indicators to predict absolute poverty based on expenditures (van Edig 2006, van Edig et al. 2007). The first objective of my research was to find the extent to which these models are robust over time in terms of prediction power (Chapter 2) and indicator composition (Chapter 3). The second model (Model 2) I tested further, analyzing prediction accuracy among three groups: the chronic poor, transient poor, and never poor. Due to the fact that the model uses mostly long-term indicators, it seemed likely that lower accuracy would be seen for the group belonging to the transient poor (Chapter 3).

In addition, an indicator based poverty assessment tool provided by the IRIS[2] Center and USAID[3] for Indonesia is evaluated here using the data set from Central Sulawesi. USAID requires its partners - especially those working with micro-enterprises to reduce poverty - to assess their target population with these tools, so it is important to test how well the tools work in practice (Chapter 2).

[2] IRIS is a research and advisory centre at the Department of Economics, University of Maryland.
[3] USAID is the U.S. Agency for International Development.

The research questions addressed in Chapters 2 and 3, can be summarized as follows:

1. Is a regionally calibrated poverty assessment tool robust over time?
2. Is a nationally calibrated poverty assessment tool robust over space?
3. How does the indicator composition of the regional tools change when models are re-estimated?
4. Does an easily applicable poverty assessment tool like Model 2 overlook the transient poor?

The second objective of this study addresses poverty dynamics in Indonesia, focusing on the household characteristics determinants of chronic and transitory poverty. A poverty dynamics analysis was performed using panel data from two expenditure surveys in 2005 and 2007. During this period households both escaped from and fell into poverty, an important consideration in assessing poverty reduction strategies and how to target these strategies specifically toward the transient or chronic poor. Potential poverty reduction projects in Central Sulawesi should know what type of poverty they are dealing with because different strategies are more effective for addressing transient poverty and others are more appropriate for chronic poverty. Chapter 4 gives a general picture of the poverty situation in the research area using several poverty measures I calculated for both years. Furthermore, I created a transition matrix including both international poverty lines (1 and 2$ US) to show movement into and out of poverty. To trace underlying determinants of chronic and transitory poverty, I conducted multinomial logit regression analyses. My work adds a current, albeit regionally focused, analysis to the study of poverty dynamics in Indonesia.

The research questions answered in Chapter 4 are the following:

5. How did the poverty situation in the vicinity of the Lore Lindu National Park change between 2005 and 2007?
6. How dynamic is poverty in the research area?
7. What are the determinants of chronic/ transient poverty?

My third objective in this study was to analyze the link between poverty and deforestation in the vicinity of the Lore Lindu National Park. Further study of the extent of forest clearance by rural farmers is important as shown by a statement made by The Nature Conservancy (TNC, 2005a) that the conversion of forest into farm land is mainly driven by small-holders and that poverty in the surrounding villages threatens Lore Lindu National Park. My study traced household characteristics determining forest clearance. Factors influencing if forest is cleared and the size of cleared plots were analyzed using probit and tobit regression analysis. In addition, I investigated the types of crops – cash or subsistence – grown in formerly forested plots.

Because poverty is assumed to be a major driving force in deforestation, a relative poverty index (by Abu Shaban 2001 based on the poverty assessment tool by CGAP[4], further explained in Chapter 5) is included as an independent variable in the regression analysis, and the corresponding poverty categories ‘poorest’, ‘poor’, and ‘less poor’ were used to group the descriptive statistics. The data used for the study was household survey data from STORMA subproject A4 (see section 1.3) from 2000/2001, 2004, and 2006. In summary, Chapter 6 deals with the following questions:

8. How much natural forest was cleared by rural households between 1999 and 2006?
9. What crops are grown on these plots?
10. Are there notable differences between poor and wealthier households?
11. What are the influential factors determining decisions to clear natural forest?
12. What determines the extent of forest area cleared?

Thus the study contains seven chapters: In the introductory Chapter 1 an overview on the research background and underlying theoretical concepts is given. Chapter 2 contains an analysis of the robustness of indicator based poverty assessment tools in changing environments. Chapter 3 provides a connection between the topic of operational poverty assessment using a small set of indicators and the analysis of poverty dynamics. This chapter also presents a re-estimation of both models. Chapter 4 gives an analysis of short-term poverty dynamics in rural Central Sulawesi’ households between 2005 and 2007. In Chapter 5, the link between rural poverty and deforestation is examined in detail. In Chapter 6, all results are summarized and overall conclusions are drawn.

[4] CGAP is the Consultative Group to Assist the Poorest.

1.3 The case of Indonesia

Indonesia is the world's largest archipelagic state. It consists of over 17,500 islands, roughly 6000 of which are inhabited (CIA 2009). The CIA's World Fact book estimates the Indonesian population at slightly more than 240,270,000 with an annual growth rate of 1.1%. Forty eight percent of the population lives in rural areas. In 2008 the gross domestic product (GDP) was estimated at 916,7 billion $US in purchasing power parity (PPP), and the annual growth rate was 6.1%. The 2009 Human Development Report reports the GDP per capita at 3172 $US PPP for 2007. Agriculture makes up 14.4% of the GDP, industry 48.1% and services 37.5% (estimates from 2008). Nonetheless, 41.2% of the population is still employed in agriculture; whereas, only 18.6% of the working population is employed in industry, and 37.5% in the tertiary sector (CIA 2009).

The Human Development Index (HDI), a composite measure including three dimension of well-being – namely a long and healthy life, a decent living standard and access to education – is reported at 0.734, giving Indonesia a rank of 111 out of 182 countries for 2007. This places Indonesia in the category of medium developed countries (HDR, 2009).

The research area for this study is located on the island of Sulawesi, one of five largest Indonesian islands (UNDP 2005). More precisely, it is located in Central Sulawesi, just at the south of the equator in the vicinity of the Lore Lindu National Park (LLNP). The Park itself harbors some of the last intact forest tracks in Sulawesi, but suffers from illegal logging (Rhee et al. 2004). More than 100 villages with approximately 120,000 inhabitants are located in the vicinity of the park (ANZDEC 1997). The park provides water resources for about 300,000 people in the area. The area surrounding the park has been used largely for agricultural cultivation during the last 100 years. High rates of migration in the last two decades have contributed to growing population pressure on natural resources, including rainforest margins (Kreisel et al. 2004). Although villagers have traditionally used the park, continued illegal harvesting of forest resources and agricultural expansion threatens wildlife and forest ecosystems. This process is largely driven by severe poverty in the surrounding villages (TNC 2005a).

The research program Stability of Rainforest Margins in Indonesia (STORMA) provided the framework for conducting field work and gathering the empirical data presented in this report. STORMA was an interdisciplinary research program funded by the German Research Foundation (Deutsche Forschungsgemeinschaft, DFG). One of the main research objectives of this program was: to study the process of changing land use systems across Indonesia and to analyze more specifically how the integrity of LLNP may be threatened by the expansion of land used for farming. STORMA was a collaborative research project by the German Georg-August-University Göttingen and University of Kassel and the Indonesian universities Universitas Tadulako Palu and Institut Pertanian Bogor. In addition to its concentration on scientific research, STORMA seeks to provide information that will be useful to decision makers and relevant in the development of related policies (Zeller et al. 2002). The research on rural poverty presented here was undertaken within sub-project A4, which focuses on the economic analysis of land use systems of rural households.

1.3.1 Poverty in Indonesia

In a 1992 speech given by President Soeharto the issue of poverty in Indonesia was finally brought to the forefront. The president announced that in the year 1990, 15% of Indonesia's total population lived in poverty, making the matter one of public concern across the nation. Although the discussion on inequality had been openly ongoing for two decades before this speech, the discussion had been focused on disparities in the distribution of wealth generated by economic growth (Asra 1999). Since the 1960s, poverty reduction has been largely subsumed by the promotion of overall economic development (Schwinghammer 1997).

In the early years of President Soeharto's leadership (beginning in 1967), Indonesia faced impressive economic growth largely due to growing overseas demand for Indonesia's industrial raw materials (Asra 2000). This economic growth was associated with a reduction of overall poverty in Indonesia (Schwinghammer 1997, Sumarto et al. 2004). From 1970 to 1996 the Indonesian economy was characterized by impressive economic growth, a decline of poverty (from 40% in 1976 to 11% in 1996) and apparent structural changes in Indonesia's economy (Asra 2000).

In mid 1997 Indonesia and many other Asian countries faced a severe financial crisis leading to widespread economic distortions. During this crisis, the headcount poverty rate increased quickly in Indonesia (Widyanti et al. 2001). According to Suryahadi et al. (2001), the headcount poverty rate rose from 15.6% in February 1996 to 27.1% in February 1999. In rural areas the poverty rate increased by about three quarters (Suryahadi et al. 2001).

Admittedly, not all regions were affected in the same way. The island of Java and urban areas were harder hit than rural areas and remote islands (Brodjonegoro 2002), indication of the large regional disparities within the country. Regional disparities also appear within Indonesia's overall development: even when the economy has grown rapidly, not all parts of the country have benefited (Daimon 2001).

Since mid 1998, Indonesia has restored its financial and economic stability, and domestic prices and real wages have recovered (Widyanti et al. 2001). After the crisis, poverty decreased as the economic situation stabilized. Therefore, many households faced only short term or transitory poverty. It is estimated that 40% of Indonesian households experienced periods of poverty during the crisis (Widyanti et al. 2001). Nonetheless, rates of chronic poverty increased from 3.2 to 9.5% during the crisis, and the number of vulnerable households, or those with a high risk of becoming poor in near future, tripled during this period. Between 1997 and 1998, 16% of the rural population moved from being non-poor to being poor (Suryahadi et al. 2001). Altogether, "the pre-crisis poverty rate doubled during the crisis" (Widyanti et al. 2001, p. 6). However, after poverty rates in Indonesia came down to the pre-economic crisis level in 2005, the situation worsened again due to rising food prices (World Bank 2008).

Using the international poverty line of 1$ US in PPP, the Human Development Report (2007/2008) gives a poverty headcount of 7.5% for Indonesia. In Table 1, national and international headcount poverty rates for Indonesia are summarized.

Table 1: Percentage of Indonesian population below different poverty lines

Poverty line	Year	Headcount index (%)
National	1996	15.7
National	1999	27.1
National	2000-2006	16.7
1 US$ PPP	2002	7.5
2 US$	2002	52.4

Source: World Bank 2004, Pradhan et al. 2000, HDR 2009

1.3.2 Deforestation in Indonesia

Forest covers 48% of Indonesia's total land area, with the majority of this forested land owned by the government. Although on a global scale there has been a decline in net forest cover in recent years, this has not been the case Indonesia, which was among the top 10 countries with greatest annual net forest cover loss from 2000 to 2005 (FAO 2006). While the global annual deforestation rate declined from 0.22% between 1990 and 2000, to 0.18% between 2000 and 2005, the deforestation rate in South East Asia increased from 0,8% to 1% in the same respective time periods. Deforestation rates in Indonesia are higher than those of South East Asia. In the ten year period from 1990 to 2000, 1.7% of Indonesia's forest cover was cleared; while in the following five year period from 2000 to 2005, a loss of 2% of forest cover was documented – a notable increase (FAO 2006). Primary forests are particularly threatened by such clearing. In 1990 Indonesia's forest cover was 60.2% primary forests, while in 2000 this number had dropped to 57.2%, and in 2005 primary forests only made up 55% of the country's total forest cover (FAO 2006). Seeing as Indonesia is home to about 17% of the world's animals and plant species, including many endemic species (TNC 2005) that rely heavily on forest habitats, it can be said that deforestation is threatening one of the world's hot spots of biodiversity. This is particularly true in Sulawesi, the area of focus for the research presented here: "Even in a country known for its unique natural resources, the island Sulawesi stands out as one of the most extraordinary places on earth, with an astonishing 98% of mammal species and 27% of bird species that exist nowhere else on the world" (TNC 2005, p.1).

Although the conversion of natural forest to other forms of vegetation has taken place for hundreds of years in Central Sulawesi, the process has accelerated markedly since the 1970s. This change can be traced to a combination of transmigration, crop production, and government supported commercial logging (Rhee et al. 2004).

1.4 Poverty: definitions, concepts and measurement

The following sections will discuss the underlying theoretical debates revolving around poverty concepts and definitions, present different strategies for the assessment of poverty, and explore the link between poverty and deforestation.

1.4.1 Definitions and concepts of poverty

The World Bank states on its web-page that poverty is a "call for action" (World Bank 2009). For any poverty alleviation strategy it is indispensable to define who are the poor and how poverty is measured (for summaries of approaches, concepts, and measurement of poverty see e.g. Ravaillon 1992, Lok-Dessallien 1999, Ruggeri Laderchi et al. 2003). Poverty, however, is difficult to measure and to define because it is a multidimensional phenomenon (Bourguignon and Chakravarty 2003, Hebel 2004). There is no single poverty theory that is held to be universally valid, although both the economic and the social sciences have suggested a variety of options (Hatzius and Marggraf 1994, Ruggeri Laderchi et al. 2003). Consequently, there is no uniform definition of the term "poverty" in the literature, but rather a kind of "agreement" that poor people live a life that is in some way degrading (Schubert 1994) or that poor people do not attain a certain standard of living (Ravallion 1992). Different authors arrive at different conclusions regarding the nature of poverty. Poverty can be seen as the "(…) violation of peoples most basic rights" (Simmons 1995, p. 6), a point of view held also by Townsend (2005) who refers to a human-rights related approach to poverty, and Pogge (2000) who dedicates an entire book to this rather ethical debate. In a similar sense, Ahmed (2004; p.1) states that "(p)overty refers to forms of economic, social and psychological deprivation among people (…)".

Different definitions of poverty or deprivation refer to different 'spheres of concerns': Are social, cultural or political aspects included, or does the definition of poverty only refers to material aspects? Is poverty measured with monetary approaches, in terms of utility or resources? Or is it measured, as done in the capability approach, as the freedom too live a decent life? (Ruggeri Laderchi et al. 2003).

When poverty is measured in monetary terms, as is often the case, it is assumed "that the monetary metrics either capture the essence of deprivations, or proxies all other deprivations" (Ruggeri Laderchi et al. 2003, p. 246). This view is based on a number of assumptions about well-being that are advanced by economic theory through concepts such as 'economic rationality', and 'utility maximization' (Johannsen 2009).

This purely money-metric concept has been widely criticized, with one of the most famous critics being Nobel prize winner Amartya Sen. In his book *Development as Freedom* (1999), and in several earlier publications (e.g. Sen 1985; 1988; 1992), Sen argues that poverty is not strictly a matter of low income and that the concept should rather be viewed as a deprivation of basic capabilities. Nevertheless, he also admits that low income is one of the major causes of poverty in the sense that a lack of monetary resources often results in the limitation of capabilities. Thus, he promotes plurality in welfare assessment.

In such multidimensional approaches it is important to ask how the different dimensions of poverty should be measured and how these measurements should be aggregated. In the aggregation of measurements, some information is always lost (Ruggeri Laderchi et al. 2003). For a comparison of the capability approach and the classical monetary approaches to defining poverty see e.g. Ravaillon and Lokshin (2003), Kuksly (2005), Johannsen et al. (2007), and Johannsen (2009).

In summary, poverty can be described as a "(…) state of long-term deprivation of well-being, a situation considered inadequate for a decent life. Poverty is thus synonymous with lack" (Larivière et al. 1998, p.15).

Many different conceptual approaches have been used for the measurement of well-being. For example, household income and household consumption are two commonly used measures. As widely discussed in the literature, poverty measurements based on expenditure have certain advantages over measurements based on income. There is substantial evidence that expenditures are the more stable indicator of long-term welfare. Household consumption measurements indicate long-term command over resources, providing information on both past and future income, also because households smooth varying income over time (Ravaillion 1992, Deaton 1997). Whether using income or expenditure measurements, the adjustment of price differences is crucial for the purpose of poverty comparison. A discussion on the choice of consumer price indices and the calculation of PPP can be found in Greer and Thorbecke (1986). Besides income and expenditure based measurements, levels of nutritional attainment are also commonly used for poverty comparison in developing countries (Ravallion 1992).

Poverty analyses can be conducted either on a macroeconomic or on a microeconomic level. Macroeconomic analyses deal with country level data, gathering information to find how the 'average person' of a country lives below the existence minimum, or in relation to others, not enough above it. Microeconomic analyses deal with individuals or households, who cannot satisfy their basic needs or not enough in relation to other persons (Schubert 1994). The present study is based on household level data, so I will focus on the microeconomic level in the following discussion.

In addition to the conceptual debate revolving around poverty assessment, there are a number of practical problems that should be considered when measuring poverty regardless of the conceptual approach being used. For example, although fundamentally it is the individual human being that is affected by poverty, measurements of poverty are generally taken in aggregates, assessing the problem at the household or family level (Ruggeri Laderchi et al. 2003). One method that has been suggested for dealing with this discrepancy is the construction of equivalent scales (Greer and Thorbecke 1986). In addition, consideration must be made for how poverty changes over time. During different seasons of the year or during different periods of a lifetime, people can move into and out of poverty (Ruggeri Laderchi et al. 2003). On an individual level there is a very important difference between being poor for a limited period of time and facing a situation of chronic poverty (Witt 1998).

1.4.2 Absolute versus relative poverty

In any discussion of poverty assessment it is important to distinguish between absolute and relative measurements. The term ‘absolute’ indicates that people are identified as poor in relation to a defined scale and not in comparison to other people’s situation. An absolute poverty measurement begins by defining a minimum living standard, often referred to as existence minimum. The most crucial component of any absolute poverty measurement is the definition of an existence minimum or minimum standard of basic needs *ex ante* (Witt 1998). When operating under the concept of absolute poverty, there is no variation in the level of poverty relative to overall living standards. This is especially relevant for low-income countries (Ravallion 1992) where it is often the case that “the availability of a survival minimum is felt as a pressing issue” (Ruggeri Laderchi et al. 2003, p. 246).

Approaches to defining an existence minimum can be divided into the two types, a direct and indirect one. The direct approach sets the minimum material criteria for human subsistence, while the indirect approach may define the minimum income necessary to purchase the material goods needed to lead a decent life (Schubert 1994). But what are these criteria? Neither the goods, which guarantee physical or biological subsistence, nor the income that provides a supply of these goods, are definable without considering the social environment and the value system of the society (Hatzius and

Marggraf 1994). Thus, the household welfare level that is chosen to be the threshold for poverty is simply a social convention (Pradhan et al. 2000). Or, as Ruggeri Laderchi et al. (2003) put it, "(d)ifferent interpretations of reality translate into different poverty measures" (p. 244). Sen (1979) argues against this view of poverty, referring to it as a 'value judgment.' He argues that "there is a difference between saying that the exercise is a prescriptive one from saying that the exercise must take note of the prescriptions made by members of the community." (p.285). In my study, Chapters 2 and 3 make use of the concept of absolute poverty.

In contrast, relative poverty measurements define the situation of an individual or the situation of a group of persons in relation to the average living standard of the society they live in or in relation to other members of the society. Thus the focus lies on economic inequality within a defined population. In theory, relative poverty is only eliminated if wealth in a society is distributed in a perfectly equal manner (Witt 1998).

From a political perspective, relative poverty measurements can be useful on a national level for assessing the effectiveness of government programs designed to reduce inequality within the country (Ruggeri Laderchi et al. 2003).

A differentiation should be made between subjective and objective measures of relative poverty. This differentiation mainly refer to whether qualitative or quantitative approaches are employed. Relative poverty can be measured subjectively using personal interviews that ask individuals to rank themselves in relation to others. Results from such interviews can be difficult to interpret. Objective measurements often use subsistence criteria, income related methods or a combination of measurements reflective of regional well-being. For example, an objective measurement of relative poverty could be taken by comparing a household's financial resources to an average income threshold for the defined region (Schubert 1994, Lok-Dessallien 1999).

This is often problematic because certain value judgments are inevitably made in both the choice of reference and the choice of critical values set to define the allowance for differences within a society (Schubert 1994, Lok-Dessallien 1999). In my study, Chapter 5 utilizes the concept of relative poverty.

1.4.3 Poverty lines

Poverty lines are established to divide the poor from the non-poor often form the basis of poverty measurements (Ahmed 2004). Goedhart et al. (1977) state that, "(i)n simpler language, we may say that welfare is defined in terms of command over real goods and service-command over resources, for short. The less command one has over resources, the less welfare one enjoys; that is, the poorer one is. Poverty is then defined as a situation where command over resources falls below a certain level, *the poverty line*" (p. 504). There are different ways to set a poverty line, and as Ravallion (1992) says, "poverty lines exist, but views differ on their location" (p. 25). Here again, a distinction is made between absolute and relative poverty measurements (Ravallion 1998). In practice, however, a certain amount of arbitrariness is unavoidable in defining any poverty line (Ravallion 1992).

Absolute poverty lines are fixed in terms of a determined set of living standard indicators for the entire region targeted by the poverty study. It is important to note that poverty lines differ between countries as well as between urban and rural areas (Ravallion 1992). "The most common approach in defining an absolute poverty line is to estimate the costs of a bundle of goods deemed to assure that basic consumption needs are met in the specific domain (…)"(Ravallion 1992, p. 26). For developing countries, the food expenditures needed for a recommended food energy intake are often considered fundamental in the setting of a poverty line, and some additional non-food goods are also considered very important (Ravallion 1992). Absolute poverty lines can be calculated according to a variety of methods. For example, the Direct Calorie Intake method (DCI) considers a household poor if the per capita energy intake is less than the standard per capita energy requirement; the Food Energy Intake method (FEI) estimates the poverty line at the level of consumption or income at which households are expected to satisfy the normative nutritional requirement (see for example Ravaillon, 1998, Ahmed 2004); and, the Cost of Basic Needs method (CBN), developed primarily by Rowntree (1901), sets the poverty line according to the cost of an appropriate bundle of goods to ensure the fulfillment of basic predetermined nutrition and non-food requirements. The latter method is most widely used in developing countries; in fact, in Indonesia the BSP (Badan - former Biro - Pusat Statistik, the Central Statistic Agency) uses the CBN method to calculate national poverty lines (Maksun 2004)[5].

The international poverty line of 1$/day, which I use in Chapters 2 and 4, "(…) was constructed by researchers of the World Bank in 1990 as the median of the lowest ten

[5] The data used to compute the poverty line is taken from the SUSENAS (Survei Sosial Ekonomi Nasional) survey, a representative large scale survey (Asra 2000).

national poverty lines available in a sample of 33 countries" (Kakwani 2006, p. 21). This line was adjusted to 1.25$/day in 2009 and is still used for international comparisons.

When performing relative poverty measurements, most 'critical values' are determined according to income or capital related thresholds. For example, the bottom quintile of the income distribution, or an income less than 40% of the average income of the society, could be designated as a critical value (Schubert 1994, Lok-Dessallien 1999). Relative poverty lines are applied mostly in industrialized countries. The EU member states set their level of low income to "(…) a household income below 60% of the contemporary, national, median household income before deducting housing costs" (Poverty Site 2010).

The term 'poverty analysis' refers to a range of poverty measurements, such as the Foster-Greer-Thorbecke indices (Foster et al.1984). The poverty analysis measurements used in this study are described in the corresponding chapters, so the issue will not be further examined here.

1.4.4 Transient versus chronic poverty

The differentiation between transient and chronic poverty not only matters for the empirical measurement of poverty, but also in terms of targeting. Poverty reduction projects or programs need to know with which 'kind' of poverty they are dealing as appropriate poverty reduction strategies differ between the chronic and the transient poor (Grootaert et al. 1995, Jalan and Ravaillion 2000, Hulme and Shepherd 2003, and McKay and Lawson 2003).

The terms 'chronic poor' and 'transient poor' are used to differentiate between those who are poor for all or most of their lifetime, and those who move in and out of poverty over time. The 'spells' approach and the 'components' approach are two common methods used to identify chronic and transient poverty. The spells approach defines as chronically poor any household that falls below the poverty line in every period of data collection (see e.g. McKay and Lawson, 2003). The components approach attempts to isolate the underlying components of poverty from transition shifts taking measurements of the average income/consumption over a period of time or predicting income based on known household characteristics (Hulme and Shepherd, 2003). Further information on both approaches can be found in Chapter 4 of this study.

The importance of targeting poverty reduction strategies can be seen in the different needs of the chronic and transient poor: the chronic poor need programs that enhance their physical and human capital endowments; whereas the transitory poor need help to overcome difficult situations (Grootaert et al. 1995). Thus, the direct transfer of income or assets could help the chronic poor; whereas insurance or income stabilization programs are particularly suited for protecting the transient poor (e.g. Baulch and Hoddinott, 2000). To reduce transitory poverty Hulme and Shepherd (2003) point out that pressing issues for policy makers should be the implementation of: pensions for the elderly, unemployment, illness and disability insurances, direct aid in emergency situations, and access to credit.

1.4.5 The assessment of poverty

There have been a variety of attempts to devise a method of poverty assessment that treats poverty as a multidimensional phenomenon rather than simply a measurement of inadequate income or expenditures (Osmani 2003). Nonetheless, it is clear that poverty assessment faces both methodological and conceptual challenges (Ravallion 1992). Zeller et al. (2001) mention three general approaches for assessing poverty. First, they describe the "construction of a poverty line and computation of various measures that take into account the way in which household expenditures fall short of the poverty line" (ibid. p. 3). In this approach the total household expenditures are used to evaluate a household or individual's living standard. The question is whether the household income is sufficient to meet basic needs. This "basket of foods and services corresponding with the local consumption pattern and satisfying a pre-set level of basic needs for one person is constructed and ranked at local consumer prices to compute its minimum costs" (Zeller et al. 2001, p. 3-4). The value of this basket represents the poverty line, generally given as a daily per capita expenditure. This method of poverty assessment is widely used by national governments. According to Zeller et al. (2001), the disadvantages of this method are the large data requirements, problems related to the recall method for food and non-food expenditures, and problems related to the verifiability of the expenditure data. Moreover, the analysis of expenditure data requires advanced skills in statistics. The Living Standard Measurement Survey (LSMS) of the World Bank is a widely recognized example of this kind of assessment. LSMS's are large-scale surveys which aim to satisfy the data requirements of decision makers as well as monitor and evaluate the impact of development policies. The LSMS contains four multidisciplinary questionnaires that each cover different aspects of well-being. The data gathered gives a general picture of the household situation and behavior, allowing for the household living standard to be monitored and evaluated (Lariviére et al. 1998, Grosh and Glewwe 2002, Deaton 1997). When income and expenditure are measured directly through detailed social-economic surveys, as in the LSMS, one can speak of *sophisticated means tests* used in targeting poverty reduction programs (Johannsen 2009).

Additional approaches to poverty assessment described by Zeller et al. (2001) include the Rapid Appraisal (RA) and the Participatory Appraisal (PA) methods, both of which use input from community members. RA and PA are subjective approaches to measuring relative poverty which ask people to rank their status in relation to other community members. Both appraisals use techniques like 'wealth ranking' (see for example Feulefack et al. 2006) and 'community mapping'. While the object of the PA is to empower a targeted group, the RA seeks to provide data about a community in a relatively short period of time. Both approaches require participation from community members, but each has different time requirements. The Participatory Appraisal as well as the Rapid Appraisal have a high value for the identification of vulnerable groups within a community. For a general poverty assessment for a region, a nation or for international comparison these approaches are not applicable due to the difficulty of verifying the subjective rating of community members on this kind of scale and the complications presented by the need for skilled communicators to conduct the surveys. Furthermore, these relative assessments are not suitable for comparative studies because wealth levels in different societies are not comparable.

A third type of poverty assessment discussed by Zeller et al. (2001) is "the construction of a poverty index using a range of qualitative and quantitative indicators" (p. 3). Credible information can be obtained quickly and inexpensively with a tool of this type that uses indicators to describe different dimensions of poverty. The Human Development Index (HDI) and the Housing Index are two commonly used examples of such indicator-based poverty assessments. In the latter, indicators like 'condition of roof' are compiled and analyzed; with one possible criticism being that only one dimension of poverty is captured. Perhaps the most notable problem in using indicator based tools is the arbitrariness of the weighting of different indicators.

The CGAP's micro finance poverty assessment tool (see Henry et al. 2003) is also of the indicator based type. This tool, developed by Zeller et al. (2001; 2006) at the International Food Policy Institute (IFPRI) in cooperation with the CGAP, assesses relative poverty using Principal Component Analysis (PCA) for the selection of indicators. This methodology is designed to avoid the arbitrary selection of indicators and their corresponding weights. Chapter 5 contains an analysis based on this CGAP poverty assessment tool. It is also pertinent to note that the later discussed 'operational tools for poverty assessment' refer to the indicator based approach to poverty assessment.

Often poverty profiles are used to present the data gathered in a poverty assessment study. According to Ravallion and Badani (1994, p.75) "a poverty profile shows how a measure of poverty varies across subgroups of a population, such as region of residence or sector of employment." Poverty profiles are often used to compare socioeconomic subgroups within a given country or region in terms of the incidence, distribution, and extent of monetary poverty. The main objective in drawing a poverty profile is to give a descriptive analysis of the data gathered (Johannsen 2009).

1.4.6 Purpose of poverty assessment

Poverty assessments are mainly done for impact assessment after a poverty reduction project and for targeting purposes before implementing a project or program to reduce poverty. In the latter case the analysis is rather predictive, indicating the number of poor people to be targeted by a poverty reduction program *ex ante* (Johannsen 2009).

Many development projects focus on poverty reduction, and a wide range of policies seek to directly target the poor with services such as credit, extension, education, and transfers of cash or in-kind (e.g. Aho et al 1998, Zeller et al. 2006, Collier and Dollar 2002, Ruggeri Laderchi et al. 2003). Accurate targeting of the poor is imperative for the success of such policies and programs. Furthermore, good targeting can increase the cost-efficiency of any project (Minot 2000). Hence, a project or program that seeks to reduce poverty in a certain area should begin by finding out who belongs to the target population, i.e. who is (very) poor[6]. This is particularly important in the context of achieving the Millennium Development Goals. In the US, for example, efforts to incorporate the first MDG into national legislation were made with the passing of the

[6] The term 'very poor' here refers to those living on less then 1 $ US PPP per capita per day. The term 'poor' refers to those beneath the 2 Dollar poverty line.

'Micro-enterprise for Self-Reliance Act' (2000) and its amendment in 2003. This act requires that micro finance institutions (MFI) receiving funds from USAID report the share of resources allocated to the 'very poor' as well as the number of 'very poor' clients being served, with poverty being measured in terms of expenditure. Such a mandate requires appropriate instruments for measuring expenditure poverty (van Bastelaer and Zeller 2006, Johannsen 2009).

Since it is time consuming and costly to assess expenditure poverty using large scale surveys such as the LSMS, it is useful to have tools or instruments that allow for an easier selection of a target group, such as absolute poor households. In addition, it can be difficult to determine whether projects have reached their poverty alleviation goals if there are no low-cost tools for monitoring and assessment (van Bastelaer and Zeller 2006).

Proxy-means tests are one alternative to large scale surveys. These tests are "based on the calculation of household welfare scores or the direct prediction of income or expenditures by means of proxy indicators on household characteristics other than income or expenditures" (Johannsen 2009, pp. 35-36). Thus, certain types of proxy-means tests, i.e. operational poverty assessment tools, can be used to estimate household expenditures by use of a small set of reliable indicators.

There were several studies on proxy means test, ranging from simple tools (household size or size of the first loan) without any weighting system to tools using externally set weights like the Housing Index method (Johannsen 2009).

A general conceptual framework for choosing proxy indicators has been suggested by Haddad et al. (1994). Two very important factors for operational poverty assessment tools are the accuracy of the indicator-sets' prediction capability, and the cost and practicality of data collection and verification (Johannsen 2009).

Most indicator-based poverty assessments done in the last 25 years assessed relative poverty (Zeller 2004). The majority were proxy-means tests based on the calculation of welfare index scores designed to represent a household's long-term wealth (Johannsen 2009). A few examples of indicator-based assessments (in terms of welfare indices) can be seen in the asset index by Filmer and Pritchett (2001), the earlier mentioned CGAP poverty assessment tool by Zeller et al. (2001), and the wealth indices developed by Sahn and Stiefel (2000), and Montgomery et al. (2000).

Grootaert and Braithwaite (1998) used a different approach in their research on correlates of poverty and indicator-based targeting in Eastern Europe in which they used a relative poverty line for the analysis. In their study, multivariate regression analysis was used to detect determinants of poverty. They found a strong relationship between poverty and the number of children in a household, as well as evidence indicating that poverty in Eastern Europe has age and gender dimensions.

This example belongs to a range of approaches that aim to directly predict expenditures or income. Different studies have employed a variety of strategies for indicator selection, ranging from manual selection to purely data-driven screening processes, to mixtures of manual and data-driven screening, to theoretical explanatory modeling (Johannsen 2009). A few exemplary studies include: Grosh and Baker's (1995) comparative analysis of proxy-means tests for Latin America, Ahmed and Bouis's (2002) proxy-means test to evaluate food subsidies in Egypt, Copestake et al. (2005) and their assessment of the outreach of Micro Finance Institutions (MFI) in Peru using proxy-means tests, and Schreiner's poverty assessment tools developed for several countries, including Vietnam (2008). For further reading, a more detailed summary on proxy-means tests can be found in Johnannsen (2009).

A recently developed approach by Alcaraz V. and Zeller (2008) assesses a household's poverty status via food security scales. Three different scales – non food insecure, moderately food insecure and severely food insecure – are used to predict daily per capita expenditures. The main problem here is that food insecurity is not always indicative of (income) poverty. This shortcoming has already been addressed by Suryanarayana and Silva (2007), who found that in India targeting the expenditure poor and the food insecure have significantly different results.

In Chapter 2 of my study I discuss an approach that aims to assess absolute expenditure poverty in terms of the money-metric international poverty line. The poverty assessment tools used estimate daily per capita expenditures based on a set 15 indicators (see also van Edig 2006, van Edig et al. 2007). In contrast to the causal analysis of poverty changes over time, the character of this analysis is mainly predictive. The indicators and the weights of the coefficients were validated using several accuracy measures. Indicators were selected by applying OLS and quantile regression techniques. The methodology used avoids both the arbitrary selection of indicators and the application of external sampling weights (Johannsen, 2006). More details are given in Chapter 2.

1.4.7 The link between poverty an deforestation

The literature reveals two opposing views commonly held regarding the link between poverty and deforestation: some argue that the poor play a significant role in deforestation, while others hold that the poor have strong incentive to protect forested land. The conversion of forest into agricultural land is widely held to be one of the most important immediate causes of deforestation (Geist and Lambin 2002, FAO 2006). In 38% of the Asian studies analyzed by Geist and Lambin (2002), the prevalent cause of deforestation was found to be a combination of agricultural expansion, wood extraction, and infrastructure expansion. Regarding the expansion of agricultural land, Geist and Lambin (2002) state that "in permanent cultivation, the expansion of food-crop cultivation for subsistence is three times more frequently reported than the expansion of commercial farming" (p. 145). This finding suggests that poor farmers who rely on subsistence production do contribute to deforestation.

In contrast, the Poverty and Environment Network (PEN, 2009) argues that forests are often crucial for people's livelihoods: they can support subsistence, generate cash income, and act as safety networks. Furthermore, forest resources can fill gaps as part of the *ex ante* response to risks by overcoming seasonal fluctuations in the availability and affordability of goods. Forests also provide a form of insurance against larger shocks such as droughts *ex post* (Wunder 2001). Thus it is argued that poor rural households have reason to protect forested areas because the clearing of forest for agricultural purposes diminishes the availability of valued forest resources.

2. The robustness of indicator based poverty assessment tools in changing environments - Empirical evidence from Indonesia[7]

Summary

Eradicating poverty is one of the highest priorities of development policies. Besides the necessary improvement of people's livelihoods, the reduction of poverty is believed to have a positive effect on the stability of the rainforest margins. Better-off households are furthermore less vulnerable to shocks caused by natural hazards.

Organizations aiming to reduce poverty need simple and stable tools to detect (very) poor households. To reliably distinguish poor people, such tools need to be easy to apply and robust in time. Using data from Central Sulawesi, Indonesia, this study aims to test first whether two sets of poverty indicators developed in 2005 are still capable in predicting absolute poverty and second, how the national calibrated tool developed by IRIS predicts poverty using the same data-set.

In 2005 and 2007, almost 20% of the rural population of Central Sulawesi was identified as being very poor with individuals living on less than $1 US per capita and day in purchasing power parities. Beside this relatively high poverty incidence compared to Indonesian average of 7.5%, the tropical rainforest in the research area is threatened by smallholder conversion of forest into farmland.

For the analysis, data from two household surveys were used. In 2005 we surveyed 264 households in the vicinity of the Lore Lindu National Park in Central Sulawesi to obtain indicators of poverty and to derive the daily per capita consumption expenditures. In total 280 indicators were recorded. Two different multivariate regression models were fit to this data-set. One model (Model 1) included all sampled indicators and the other one (Model 2) contained only easily assessable indicators as ranked by local staff. Each of the models yielded a different set of 15 indicators to best predict poverty. In 2007, we conducted an additional survey with the identical questionnaires in the same households. We used the data from 2007 to estimate the poverty status of the households with the indicators derived in 2005. Furthermore, we tested the national

[7] by X. van Edig, S. Schwarze, and M. Zeller (2010) in T. Tscharntke, C. Leuschner, E. Veldkamp, H. Faust, E. Guhardja, and A. Biddin (eds.) Tropical Rainforests and Agroforests under Global Change. Ecological and Socio-economic Valuations, Springer, Berlin, Heidelberg, pp. 191-211, original publication on www.springerlink.com.

calibrated poverty assessment tool developed by The IRIS Centre and USAID[8] with the 2007 household data from Central Sulawesi.

As to the results, we can state that both tools calibrated for Central Sulawesi in 2005 lose accuracy because they tend to over-predict the poor. The *Poverty Accuracy* of both tools declined between about 0.5% and 21%. Only in the case of one-step OLS of Model 2 the *Poverty Accuracy* increased by about 10%. Instead the accuracy performance of the national calibrated tool provided by IRIS and USAID are overall disappointing.

2.1 Problem setting

2.1.1 The need for poverty reduction in economical and ecological terms

Although the first millennium development goal of the United Nations is to reduce extreme poverty and hunger by half until 2015 (United Nations 2008), that goal has yet to be achieved and poverty remains a pervasive problem in many countries. In general, poverty reduction is one of the main goals of development policies, programs and projects (e.g. Zeller et al. 2001, Collier and Dollar 2002). In Central Sulawesi we found that almost 20% of the households are very poor, i.e. the household members live on less than $1 US purchasing power parities (PPP) per capita and day. This poverty headcount is quite high in comparison to the Indonesian average of 7.5% (HDR 2007/2008).

In Indonesia, the annual deforestation rate rose from 1.2% in the 1990s to 2.0% from 2000 through to 2005 (FAO 2009). Erasmi et al. (2004) give the research area an annual deforestation rate of 0.6% on data from 1972-2001. Schwarze et al. (2005) find a positive correlation between the relative poverty status of a household and forest encroachment. The Nature Conservancy (2005) state that the natural forest in Central Sulawesi is threatened by smallholder conversion of forest into farmland. At the rainforest margin of the Lore Lindu National Park, land use change is mainly driven by a change of strategy from "food crops first" to "cash crops first" (Weber et al. 2007).

This is in part from the Bugi migrants who brought knowledge of cocoa cultivation into the region and the desire by the indigenous population to also gain the economic benefits of cacao-production. The local ethnic groups often sell their land to the Bugi

[8] United States Agency for International Development

migrants and clear new plots in the forest for themselves (Weber et al. 2007). This is further evidence that forest degradation is often fostered by poverty combined with internal and external change factors such as population pressure as described by Wunder (2001). Poor people often clear forest areas for short term gains, even if they are aware of the long term negative effects this could have (Eckholm et al. 1984). Hence, poverty reduction in Central Sulawesi could not only improve peoples' livelihoods but also contribute to the achievement of conservation goals.

Beside their important ecological role forests are often crucial for people's livelihoods. They can support subsistence, generate income or act as safety networks. Therefore, forests are often extensively used by rural households. Thus, clearing forest areas to increase arable land can also have a negative impact as it diminishes the availability of the forest as a resource (PEN 2009). In the research area 76% of the households collect forest products, mostly firewood. However for the poorest people in the region the sale of rattan is an important income source (Schwarze et al. 2007).

Moreover, forests provide environmental services - such as coffee pollination (see for example Olschewski et al. 2007).

Furthermore, forests can fill gaps as part of the response to *ex ante* risks, e.g. to overcome seasonal fluctuations in the availability and affordability of goods. Moreover, they can act as a form of insurance for larger *ex post* shocks such as droughts (Wunder 2001). Such shocks can get more frequent and severe due to climate change. It is assumed that climate change, which deforestation contributes to, affects poor people more severely than wealthy people (IPCC 2001, OECD 2009). Therefore, forests are not only important for the global eco- and climatic systems but also important for the livelihood of rural people.

The picture drawn above clearly shows the need for poverty alleviation for both economical and ecological reasons. To better target poor households with poverty reduction programs, organizations aiming to provide these projects need good instruments to detect poor households.

2.1.2 The need for poverty assessment tools (PATs)

Several attempts in poverty assessment try to meet poverty as a multidimensional phenomenon in contrast to a pure measure of inadequate income or expenditures (Osmani 2003). In his book "Development as freedom" (1999) A. Sen argues that poverty rather is a deprivation of basic capabilities and not only a matter of the lowness of income. Nevertheless, he also admits that low income is one of the major causes of poverty in the sense that it is often a reason for capability deprivation. Hence, it is necessary to use approaches which account for low incomes and other forms of deprivation.

To better target absolute poor households easy applicable tools for poverty assessment are needed. For non-governmental organizations (NGOs) and other stakeholders concerned with poverty reduction, it is particularly important that tools which enable the detection of absolute poor households are low in costs and contain indicators which are robust over time and space.

Most poverty assessments done in the last 25 years referred to relative poverty (Zeller 2004). The concept of relative poverty defines the situation of an individual or the situation of a group of persons in relation to the average living standard of their society (see for example Foster 1998, Witt 1998). For example, Grootaert and Braithwaite (1998) conducted research on correlates of poverty and indicator based targeting in Eastern Europe using a relative poverty line for their analysis. In this study they used multivariate regression analysis to detect determinants of poverty. They found that a strong relationship between poverty incidence and the number of children in a household exists and that poverty in Eastern Europe has, to some extent, an age and gender dimension. Another example of an approach to assess relative poverty is “the construction of a poverty index using a range of qualitative and quantitative indicators” (Zeller et al. 2001, p. 3) as done by Zeller et al. (2001) using Principal Component Analysis (PCA) to derive the indicators.

Until now few attempts have been made to assess absolute poverty. One approach used is to assess a household’s poverty status via food security scales. Three different scales – ‘non food insecure’, ‘moderately food insecure’ and ‘severely food insecure’ – are used to predict daily per capita expenditures. This tool faces the problem that food insecurity is not always identical with (income) poverty (Alcaraz V. and Zeller 2008).

2.1.3 Objectives of the chapter

The aim of the survey in Central Sulawesi was to test new tools for the assessment of absolute poverty. The methodology used is based on poverty assessment tools (PATs) developed by The IRIS Centre on behalf of USAID. Out of the nine regression models tested by IRIS, two very promising types of regression models were tested in Central Sulawesi (see section 2). The study used two sets of household data. In 2005, we conducted research to identify two sets of 15 indicators each for poverty assessment in Central Sulawesi, Indonesia. We wanted to compare the capability of the models in predicting very poor households with the observed poverty headcounts.

In 2007, we conducted the same survey again to test the identified sets of indicators regarding their capability in poverty prediction and robustness over time. Furthermore, we tested a national calibrated poverty assessment tool developed and provided by The IRIS Centre and USAID with the 2007 household data from Central Sulawesi. Such poverty assessment tools are provided for over 20 different countries at URL: http://www.povertytools.org. They are approved by USAID and can be used by anyone. USAID requires its implementation partners, including organizations that deal with micro-enterprises with the aim of poverty reduction and receiving funds from USAID, to assess their target population with these tools.

2.2 Indicator based models for the assessment of absolute poverty

2.2.1 Background

One approach to assess absolute poverty was developed by The IRIS Centre at the University of Maryland in collaboration with the US Agency for International Development (USAID). These organizations developed and tested different poverty assessment tools for targeting poverty reduction projects, especially those dealing with micro-enterprises. These tools were developed in order to meet the requirements of the US Congress. In the year 2000, the US Congress adopted the *Micro enterprise for self-reliance act*. In 2003, an amendment to this act was adopted which made USAID responsible for the development and certification of low-cost poverty assessment tools. Further requirements for these tools were that they should be objective and quantitative. Hence, they should be based on income or expenditure and able to identify individuals who fall short of one of two poverty lines which were (Zeller 2004):

1. the bottom 50% of the national poverty line, or
2. the international poverty line of 1$ US PPP per day.

For further information see http://www.povertytools.org.

The approach of indicator based poverty assessment connects indicators of different dimensions of poverty with the commonly used poverty line. Indicators of poverty should – as the word indicator suggests - indicate a person's or household's standard of living or income and yield information about the social conditions of the poor (Schubert 1994, Minot 2000).

Poverty indicators can be a constitutive part in developing poverty reduction strategies as they try to measure poverty as a multidimensional phenomenon. While the indicators vary between the subjective and objective perspectives on poverty, they often have the same scale in the relative and absolute approach (Lok 1995). One problem identified is that poverty indicators face difficulties in differentiating chronic from temporary poverty. For example monetary poverty is less persistent than malnutrition or low school enrolment (Baulch and Masset 2003). Therefore monetary poverty indicators are eventually more valid for transient poor whereas indicators dealing with nutrition or education could tell more about the chronic poor. Another difficulty for poverty indicators is the seasonal fluctuation in poverty (Muller 1997). In our study we refer to the latter problem by using recall periods of at least 12 months.

A commonly used approach to assess poverty is the "construction of a poverty line and (the) computation of various measures that take into account the way in which household expenditures fall short of the poverty line" (Zeller et al. 2001, p. 3). In practice, however, total household expenditures are used as a measure to evaluate household living standard. Whether the household income is sufficient to meet food security and other basic needs is used as a criterion. The "basket of basic needs" or a monetary poverty line is applied. This "basket of foods and services corresponding with the local consumption pattern and satisfying a pre-set level of basic needs for one person is constructed and ranked at local consumer prices to compute its minimum costs" (Zeller et al. 2001, p. 3-4). The value of this basket represents the poverty line, mostly in terms of daily per capita expenditure.

2.2.2 Poverty assessment in Central Sulawesi

In the study conducted, two models for poverty assessment were tested in Central Sulawesi, Indonesia. These models search for sets of 15 poverty indicators to predict daily per capita expenditures of a certain household. For the first model (Model 1), every surveyed indicator could possibly be included. In the second model (Model 2), only indicators which were ranked as "easy to verify" by the Indonesian staff were included. Many of the variables from Model 1 were either difficult to survey or difficult to verify. The following two examples, out of the 15 indicators for Model 1 from 2005, should illustrate this: The subjective indicator "Household feels that its healthcare expenditures are above its needs" is very difficult to verify because of its subjectiveness. "The average clothing expenditures per capita in the last 12 month" instead is an objective indicator. Nevertheless, the required information is difficult to obtain and difficult to verify too. Model 2 only included indicators which were "easy to verify": E.g. "the total number of rooms in a dwelling" an indicator used for the tool, can be obtained and verified easily by the enumerator during the interview.

Why two different models? Although, Model 1 was more likely to achieve a better accuracy performance because it used all variables, Model 2 referred to two categories of problems which might occur in the analysis of indicators. First, information might be difficult to obtain, especially regarding the aspects of time, social costs and money. Second, indicators might be difficult to verify, especially if they are recall-related (Zeller et al. 2005).

A similar approach was used by Benin and Randriamamonjy (2008) to assess household income via a set of indicators in order to monitor and evaluate public investments in several countries in sub-Saharan Africa. They also used different proxy indicators in the model estimation to develop an econometric prediction model for household income.

As aforementioned, a second part of the study was to test the national calibrated tool of The IRIS Center and USAID. USAID requires its partners to use for targeting support. In general, development projects use targeting to increase their cost-efficiency (Minot 2000).

2.2.3 Accuracy measures

For purposes of assessing the prediction power of a regression model (or tool) for poverty assessment, we used the following measures of performance for each model in this study:

Total Accuracy is the percentage of households whose poverty status is correctly predicted by the regression model.

Poverty Accuracy is the percentage of very poor households whose poverty status is correctly predicted by the regression model. It is expressed as a percentage of the total amount of very poor households.

Non-poverty Accuracy: is the percentage of not very poor households whose poverty status is correctly predicted by the regression model. It is expressed as percentage of the total number of not very poor households.

Undercoverage represents the error of predicting very poor households as being not very-poor, expressed as a percentage of the total number of very poor households.

Leakage reflects the error of predicting not very poor households as very poor, expressed as a percentage of the total number of very poor households.

Poverty Incidence Error (PIE) is defined as the difference between the predicted and the actual (observed) poverty incidence (here headcount), measured in percentage points.

Balanced Poverty Accuracy Criterion (BPAC) is defined as the *Poverty Accuracy* minus the absolute difference between *Undercoverage* and *Leakage*, each expressed as a percentage of the total number of the very poor. When *Undercoverage* and *Leakage* are equal, the BPAC is equal to the *Poverty Accuracy*. BPAC is measured in percentage points (Zeller et al. 2005 /The IRIS Center 2005). The BPAC was introduced by the IRIS Center "on the assumption that a budget-constraint policy maker is interested in both correctly targeting the (very) poor by identifying the households individually and in reaching a target population similar in size to the actual poverty headcount" (Johannsen, 2006, p. 7).

The poverty line used as reference was the international poverty line of $ 1US.

2.3 Data collection and analysis

2.3.1 Obtaining expenditure data and indicators of poverty

Household surveys are the most important data source for poverty measurement and poverty comparison. They can provide direct information about the distribution of living standards in a society or in a certain region, for example how many households do not attain a certain consumption level. With the availability of such quantitative data, the poor can be assessed and an assessment of poverty policies can be done (Ravallion 1992).

The study used household data from two survey years. In both survey years, data were collected in 13 villages in the vicinity of the Lore Lindu National Park. In both years the same randomly selected households participated in the survey. In 2005, the models were estimated with data from 279 households. In 2007 data from 282 households were obtained. The intersection of both samples was 264 households.

Two questionnaires were completed in both years. One was a benchmark questionnaire to obtain the daily per capita consumption expenditures of each household and resembled the consumption module of the *Living Standard Measurement Survey* (LSMS) of the World Bank. Thus it had the same purpose of the LSMS which is to "collect information to describe poverty and monitor it over time" (Grosh and Glewwe 2000, p. 30). Thus, the benchmark questionnaire focused on the economic dimension of poverty.

Second, we used a composite questionnaire to derive indicators of poverty in several dimensions like health, education or housing. As poverty is a complex phenomenon, the composite questionnaire tried to capture different dimensions of poverty.

2.3.2 Analysis of household survey data from 2005 and 2007

2.3.2.1 Model estimation and the selection of poverty assessment indicators in 2005

In each survey year, almost 280 independent variables were compiled from the composite questionnaire. The amount of independent variables had to be reduced because of a lack of degrees of freedom for the model estimation. For this purpose several steps for the indicator selection were employed. Primarily, for Model 1 all indicators were grouped on different dimension of poverty such as education, food, durables etc. For each of these dimensions we used an ordinary least square regression (OLS) which delivered indicators for the final model estimation. For Model 2, the number of indicators was restricted by the condition of being "easy-to-verify" and there was no need for pre-selection. In each step of the indicator selection, nine control variables were forced in the model estimation: Four demographic variables controlled for demographic factors and five regional dummies controlled for agro-ecological differences. For the variable selection OLS and the MAXR routine implemented in SAS were used. MAXR seeks to maximize the R^2 considering all possible combinations of regressors. For the final selection of indicators various checks and adjustments, especially regarding the sign of the coefficient of each indicator, had to be done. The sign was expected to concur with the direction one would expect from theory. For example the indicator "share of expenditures spend on food consumption" only was included in the model if the sign of the regression coefficient was negative because, as stated in Engel's law, the expenditure share on food declines when income increases.

In addition to the control variables, we included 86 regressors in Model 1 and 90 regressors in Model 2.

To improve the accuracy of the models' different regression methods, one and two-step OLS as well as one and two-step quantile regression, were tested. For the two step regressions, two steps of indicator selection were employed with the first step identical to the OLS/MAXR- regression described above. The second step included a sub-sample which contained a higher percentage of poor households. Hence, the second step should improve the accuracy of identifying the poor.

2.3.2.2 Using the models to predict household's daily per capita expenditures

Any of the variable sets found can be described as a poverty assessment tool for the purpose of identifying the poverty status of a household. The dependent variable (per capita daily expenditures) was, like any other variable defined in monetary values (as expenditures or values of assets), converted into the natural logarithm of Indonesian Rupiah (IDR). All ordinal variables, such as the 'type of exterior wall of the dwelling', with lower values indicating inferior materials and higher values indicating superior materials, are converted into a set of dummy variables (Zeller et al. 2005).

To calculate the predicted daily per capita expenditures of household *j* the equation

$$(1)\ \ \mathrm{Y}_j = \beta_0 + \sum_{i=1}^{N} \beta_i * \chi_{ji}$$

was used, where Y_j is the natural logarithm of the daily per capita expenditures; β_0 is the intercept, β_i are the coefficients, and χ_i are the surveyed values of the indicator used in the model.

For the one-step regression the use of this equation is straightforward. For a two-step model, it is necessary to use two steps to calculate the predicted per capita expenditures. In practice this means that the second step includes only those households whose predicted daily per capita expenditures are below the expenditure percentile found during the indicator selection. For the households in our study which were predicted in the first step (one-step OLS/ one-step quantile) as having less expenditures as the 32 percentile (Model 1) or 38 percentile (Model 2), a second indicator set to predict their expenditures was applied. For all other households the predicted values from the one-step regression remained in the model.

In 2007, the indicator sets derived in 2005 were applied to the new data-set. Furthermore, the indicators proposed by IRIS for Indonesia were tested using the data from 2007.

2.3.2.3 Measurement errors and error term

Any regression model is potentially biased by measurement errors in either the dependent variable or in the independent variable. For the presented regression models the measurement error in the dependent variables is not relevant in a direct sense because the model presented is not a causal analysis but a prediction model. Nevertheless, the accuracy measures (section 2.3) could be affected because the predicted expenditures are compared to the measured expenditures. When we assume the ‘true’ equation

(2) $Y= \beta_0+\beta_1 * X_1+\varepsilon$,

where Y is the dependent variable (here per capita expenditures), β_0 is the intercept, β_1 is the regression coefficient, X_1 is the true value, and ε is error term. But what is observed is

(3) $Y^*= \beta_0+\beta_1 * X_1+(\varepsilon+ \omega)$,

whereY* is the observed dependent variable (here per capita expenditures), β_0 is the intercept, β_1 is the regression coefficient, X_1 is the true value, ε is error term and ω is the random error. In this case the estimated coefficients are not biased but the overall fit of the regression is lower and therefore the error term is larger.

A measurement error in the independent variables could be a reason for occasionally underestimating the daily per capita expenditures as we assume a true regression function of

(4) $Y= \beta_0+\beta_1 * X_1+\varepsilon$,

whereY is the dependent variable (here predicted per capita expenditures), β_0 is the intercept, β_1 is the regression coefficient, X_1 is the true value, and ε is error term. But what is observed is

(5) $Y= \beta_0+\beta_1 * X_1^*+(\varepsilon+\beta_1 * \omega)$,

where Y is the dependent variable (here predicted per capita expenditures), β_0 is the intercept, β_1 is the regression coefficient, X_1* is the observed value, ε is error term and $\beta_1 * \omega$ is the random error in the regression coefficients caused by the measurement error in X_1. In this case the measure of true X is noisy and the estimations of β_1 are biased towards 0.

In OLS regression a normal distribution of the error term, i.e. the residuals, is assumed. For our Models, we can state the residuals of the estimations are distributed normally.

2.4 Results

2.4.1 Poverty incidence in Central Sulawesi 2005 and 2007

In the research area, the number of very poor people slightly decreased from 19.3% in 2005 to 18.2 % in 2007 (Table 2). While the number of poor, i.e. those who live on less then $2 US per capita and day, increased to 59.1%. This concurs with the overall trend observed for Indonesia. The World Bank (2008) state that after the poverty rates sank to the pre-economic crisis level in 2005 and the situation worsened again after 2006 mainly due to increasing food prices.

Table 2: Percentage of poor households in Central Sulawesi using alternative definitions of poverty in 2005 and 2007

Poverty line	Poverty line (IDR per capita and day)		Headcount Index (%)	
	2005	2007	2005	2007
$1 US PPP	2723	3436	19.3	18.2
$2 US PPP	5445	6872	47	59.1

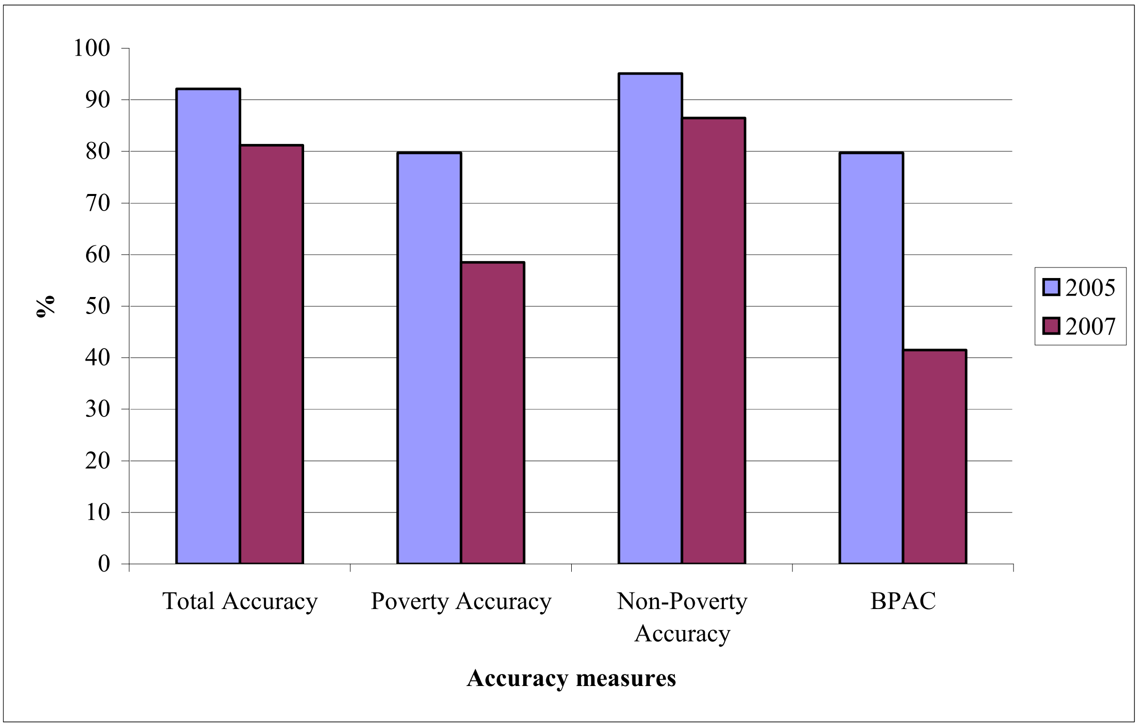
Source: own data, N= 264[9]

[9] 264 households were the intersection of both samples

2.4.2 Capability of the poverty assessment tools for Central Sulawesi developed in 2005

2.4.2.1 Model 1

The best accuracy performance in 2005 for Model 1 was achieved with a two-step quantile regression. When using the indicators selected in 2005 as well as their estimated coefficients with the data from 2007, the total accuracy dropped from 92.11% to 81.21%; the poverty accuracy dropped by about 20 percentage points from 79.69% to 58.49%. The non-poverty accuracy declined from 95.11% in 2005 to 86.46% in 2007. As both prediction errors increased – the undercoverage rose from 20.37% to 41.51% and the leakage from 20.37% to 58.49% - the BPAC decreased from 79.69 to 41.59 (Figure 2).



Source: own data, N (2005)= 279; N (2007)= 282

Figure 2: Comparison of accuracy results of Model 1 (2005-2007), two-step quantile regression

To detect which of the 2005 indicator sets – with their corresponding coefficients – fitted the 2007 data-set best, we calculated the accuracy of every tested regression method, i.e. one- and two-step OLS and one- and two-step quantile. Even if the overall accuracy of two-step quantile dropped, it remained the best way to predict the daily per capita consumption expenditures of the households and therefore poverty status of the households with Model 1.

If we only looked at the poverty accuracy, one-step OLS provided a better result in 2007 (77.36%), but the leakage was very high for this method (107.55%).

In Table 3, the corresponding indicators for the second step of the two step regressions are displayed.

Table 3. Indicators for two step regressions from 2005 of Model 1

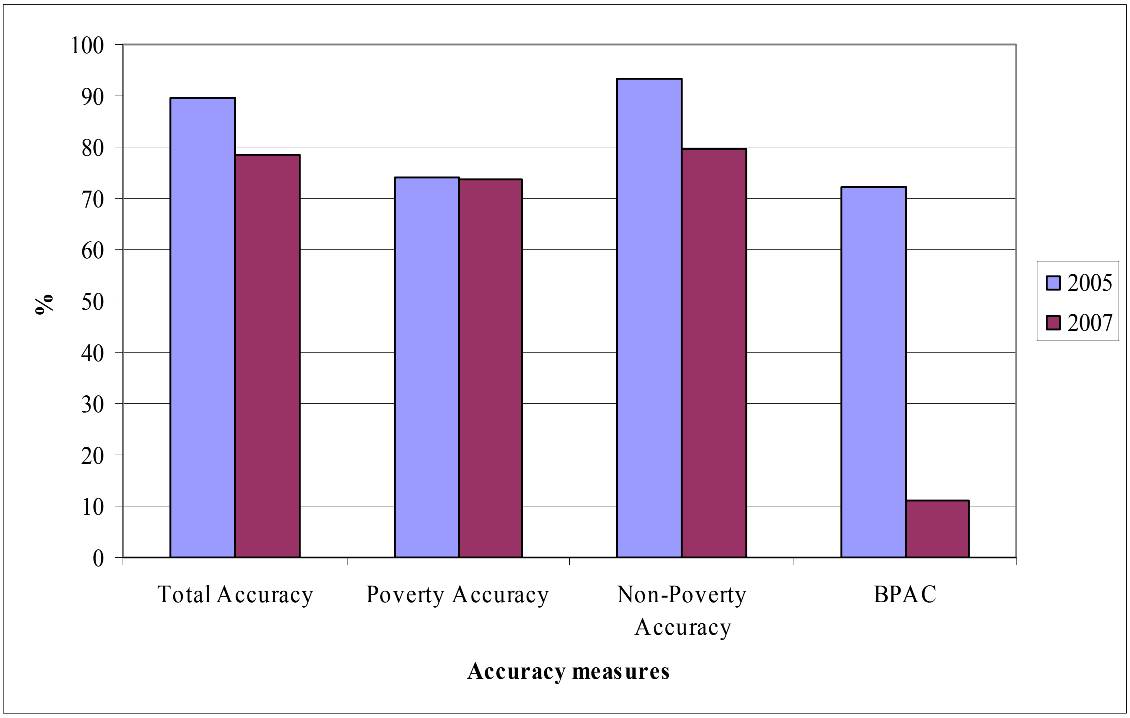
Age of household head
Age of household head squared
Household size
Household size squared
District (5 district dummies)
Dummy: Maximum education of female household member is completed secondary level
Dummy: Household member lost weight because of food scarcity in the last 12 month
Food expenditure share of total consumption expenditures in percent (from section C: summary expenditures last 12 month)
Dummy: Household eats rice mixed with maize because of food scarcity in the last 12 month
Age of youngest household member
Percentage of dependents younger than 18 and older than 60 years (in relation to household size)
Dummy: Household head works outside of agriculture
Dummy: Trunk or suitcase ownership
Total value of furniture sets owned by household
Dummy: Household agrees that people in the neighbourhood are basically honest and can be trusted
Dummy: Household borrowed money from informal market in the last three years
LOG of annualized total consumption expenditures from section C (summary expenditures last 12 month)
Total value of transportation assets
Dummy: Household made a recent home improvement
Dummy: Exterior walls are out of brick or stone

Source: own data

As discussed above, Model 1 faced several difficulties with the included indicators including the fact that rural households in the study area normally do not own a scale to monitor their weight. Therefore, the indicator “household member lost weight because of food scarcity" relies on their own impressions. As well, the indicator "food expenditure share of total consumption expenditures in percent" refers to questions in the composite questionnaire (section C) which asks for summaries of expenditures on food and non food categories. This indicator might therefore be biased by wrong guesses of the interviewed person. The dummy indicator "household agrees that people in the neighborhood are basically honest and can be trusted" was used as a proxy for social capital.

2.4.2.2 Model 2

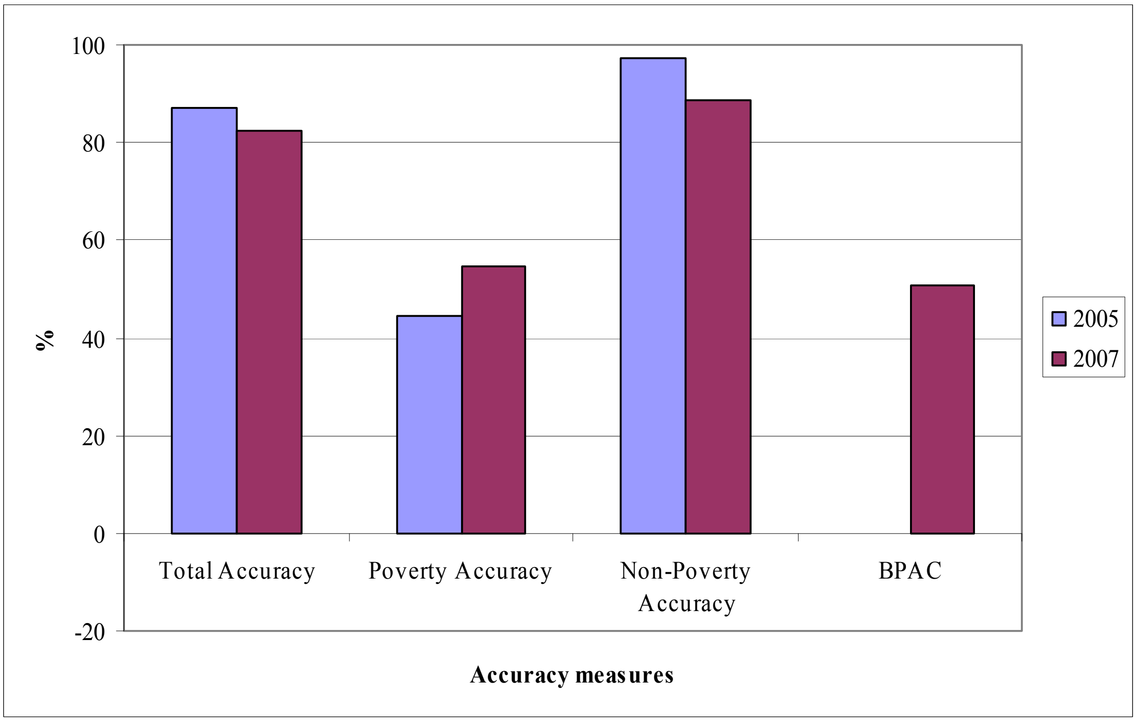
One step quantile regression provided the best accuracy results for Model 2 in 2005. In Figure 3, the accuracy results for this regression method are shown. The total accuracy decreased by 11.24 percentage points, but poverty accuracy only by 0.54 percentage points while non-poverty accuracy declined by 13.85 percentage points. As a result of increased leakage (leakage rose by 61.08 percentage points from 27.78% to 88.86%), the BPAC dropped from 72.22% to only 11.14%.



Source: own data, N (2005)= 279; N (2007)= 282

Figure 3: Comparison of accuracy results of Model 2 (2005-2007), one-step quantile regression

In 2007, one-step OLS gave the best accuracy results (Figure 4). The increase of the BPAC (from –0.01% in 2005 to 50.94%) in 2007 can be explained with the higher poverty accuracy (44.44% in 2005 and 54.72% in 2007) and the decline of the prediction error undercoverage (from 55.56'% in 2005 to 45.28% in 2007). Another reason is the increase in the error leakage from (11.11% in 2005 to 49.0% in 2007) because now both errors cancel each other out.



Source: own data, N (2005)= 279; N (2007)= 282

Figure 4: Comparison of accuracy results of Model 2 (2005-2007), one-step OLS regression

The indicators used for the one-step regression of Model 2 are summarized in Table 4.

Table 4: Indicators for one step OLS regression from 2005 of Model 2

Age of household head
Age of household head squared
Household size
Household size squared
District (5 dummies)
Total number of rooms in the dwelling
Dummy: Metal cooking pots ownership
Dummy: Clock or watch ownership
Dummy: VCD player ownership
Dummy: Motorcycle ownership
Dummy: Cow ownership
Dummy: Household uses other cooking fuel than collected wood
Dummy: Toilet is own pit toilet
Dummy: Main source of drinking water is water from well in residence yard
Dummy: Household head sleeps in bed with thin mattress out of fibers
Dummy: Household cooks in separate kitchen
Dummy: Household has own or shared electricity (including generator)
Percentage of dependents younger than 18 and older than 60 years (in relation to household size)
Dummy: Household made a recent home improvement
Number of trunks and suitcases owned

Source: own data

The indicators in Model 2 are mostly time invariable or change only very slowly over time. The potential problem with this variable set is that it might not capture short term poverty dynamics and therefore rather detects the chronic than the transitory poor.

2.4.3 Capability of the national calibrated poverty assessment tool for Indonesia provided by IRIS

IRIS is providing tools for poverty assessment by means of a small set of indicators for several countries (The IRIS Center 2008). These tools consist of the necessary questionnaires, a data entry sheet, and a data analysis tool (www.povertytools.org). The tools IRIS provides are nationally calibrated. The indicators used for Indonesia are listed in Table 5.

Table 5. Indicators from national calibrated tool

Household size
Age of household head
Household size squared
Age of household head squared
Region (Dummies for 7 different regions, Central Sulawesi is in region 5)
Dummy: Household live in rural area (the dummy for urban area was omitted because all households live in a rural area)
Dummy: Household head has incomplete secondary education
Dummy: Household head has any university education
Share of household member with incomplete secondary education
Share of household members with any university education
Dummy: Household head can read and write
Dummy: Floor of dwelling is earth
Area of the dwelling
Dummy: Main source of drinking water is bottled water
Dummy: Main source of drinking water is water from tab
Dummy: Main source of drinking water is water from pump
Dummy: Toilet facility is other (i.e. bush etc.)
Dummy: Main source of lightening is oil lamp
Dummy: Household received food aid in past 6 month
Dummy: Any household member bought new set of clothes in the previous year
Dummy: Any household member rent a stall/ shop outside of the household's dwelling

Source: IRIS (2009)

As raised earlier, IRIS and USAID are using two possible definitions of poverty lines. For the nationally calibrated poverty assessment tool developed by IRIS for Indonesia, the reference poverty line is called the median poverty line and is the bottom 50% of the national poverty line. For Indonesia this was 82,747 IDR per capita per month for rural areas. This number refers to the official national poverty line of 96,512 IDR likewise per capita per month for rural areas at 2002 prices (The IRIS Center 2008). Adjusted to the 2007 price levels by using the Consumer Price Index (CPI) the “median” poverty line per capita per month was 122,760 IDR, or 4092 IDR per day.

To measure the performance of the national calibrated tool using our data the headcount poverty rate for Sulawesi had to be calculated with the poverty line used by IRIS/USAID. (Table 6).

Table 6: Poverty rates in Central Sulawesi 2007

Poverty line	Poverty line (IDR per capita and day)	Headcount Index (%)
International poverty line of $1 US	3436	18.79
Median of national poverty line used by IRIS	4092	28.4

Source: own data/IRIS (2009); N=282

When predicting the poverty status of rural households in Central Sulawesi with our household data from 2007, but using the coefficients of the indicators listed in Table 4 provided by IRIS, the predicted headcount was 67.38%. Thus the poverty incidence error (PIE) was 38.98%. In terms of its accuracy, the performance of the tool is disappointing: the total accuracy was only 0.71%, the poverty accuracy was 0% and the non poverty accuracy 1.04%. The prediction errors undercoverage (100%) and leakage (211.11%) were very high and hence the BPAC was incredible low.

In a second calculation we used the $1 US poverty line of 3436 IDR as reference for the predictions of the IRIS tool in order to make the prediction comparable to the models described above (2.4.2) given the use of different poverty lines. In this analysis, a headcount of 11.7% was predicted by the IRIS tool. In Table 7, the observed and the predicted headcounts as well as PIE are summarized for all regression methods presented.

Table 7: Observed vs. predicted headcount

Method	Actual headcount in %	Predicted headcount in %	Poverty Incidence Error (PIE) in %
Model 1			
One-step OLS	18.79	24.27	5.48
Two-step OLS		28.36	9.51
One-step quantile		34.75	15.96
Two-step quantile		22	3.21
Model 2			
One-step OLS	18.79	19.5	0.71
Two-step OLS		20.2	1.41
One-step quantile		30.5	11.71
Two-step quantile		35.46	16.67
IRIS tool			
	18.79	11.7	7.09

Source: own data; N=282

Table 7 shows that the coefficients obtained by the one-step OLS regression method of Model 2 best predicted the poverty incidence with a PIE of only 0.71%; the second best prediction of poverty headcount by using the two-step OLS coefficients of Model 2. The national calibrated poverty assessment tool of IRIS provided the fifth best prediction of the poverty headcount. Nevertheless, the other accuracy results were disappointing: the total accuracy was only 20.92%, none of the very poor households were correctly predicted as being very poor, the non poverty accuracy was 23.69%. As well, both undercoverage and leakage were again very high.

2.5 Conclusion and discussion

NGOs, micro enterprises and other organizations or institutions concerned with poverty reduction are in need of a low-cost poverty assessment tool which is able to easily detect their clients. In the research region the role of poverty reduction is not only crucial for the improvement of people's livelihood but also for the protection of the natural rainforest. As discussed in section 1, there is a strong link between poverty and forest degradation.

In 2005, when the tools for Central Sulawesi were developed, one of the biggest problems was the trade-off between the practicability of a tool and its accuracy (van Edig 2006, van Edig et al. 2007). Johannsen and Zeller (2006) also found that the exclusion of monetary indicators (as done in Model 2) reduces the accuracy of the tool. In addition, Zeller (2004) describes another problem poverty assessment has to face: the trade-off between accuracy and costs. Our results indicate another potential weakness of poverty assessment tools: their stability over time. When predicting the poverty status of households in 2007 with 2005 indicators, the accuracy of both models tested dropped. In all cases, except two-step OLS of Model 2, the leakage increased. Thus, within two years the capability of the tools was limited by errors predicting non-poor households as being very poor. Even so the average decline in the different accuracy measures is not dramatic and, for practitioners, still sufficient.

We expected Model 1 to perform somewhat better because it includes many short-term indicators like the "number of days in last week any superior food (large fish, beef/pork/buffalo meat, chicken/duck or egg) was eaten" or the "natural logarithm of expenditures on other expenditures, social events and leisure in the last 12 months" (both examples from one-step regressions). These indicators tend to change with the same speed as household expenditures. Model 2 instead mostly used long-term variables like "total rooms of the dwelling" which do not change as fast as expenditures. In contrast to our expectations, one-step OLS of Model 2 provided the best overall accuracy. This is opposite to the findings of Zeller et al. (2005) that OLS is less able to predict the poverty incidence when the actual headcount is relatively low.

That one-step OLS of Model 2 provided the best overall accuracy is only true if we use the BPAC as benchmark. The best poverty accuracy was achieved using two-step quantile regression with for Model 2. Even if one-step OLS of Model 2 is providing the best BPAC, the poverty accuracy with this method is comparatively low (44.44% in 2005 and 54.72% in 2007). Nevertheless, the predicted poverty headcount with this method was 19.5%, which is very close to the actual headcount of 18.79%. Finally, we can state that Model 2, which could be easily applied by local organizations for targeting, is still a good choice for poverty assessment. Even if the one-step OLS coefficients provide a better BPAC, we would recommend the use of one-step quantile coefficients because they provided a better poverty accuracy (73.53%) than one-step OLS, but the leakage is not as high as with two-step quantile. This tool could be applied by practitioners straightforwardly.

In general, one could improve the methodology using a bigger sample where an out-of-sample test would be possible. An out-of-sample test would be to split a sample randomly into two parts. One of these parts would be used for the tool calibration and the second part would be used for poverty assessment.

When applying the national calibrated tool of IRIS/USAID to our data set, the accuracy of the tool is very low. This result suggests that it is very difficult, if not impossible, to develop indicator based poverty assessment tools which are applicable in all regions of a country. This seems to be particularly true in such a diverse country as Indonesia. Furthermore, we see what a huge impact the choice of the poverty line has. Therefore, the two definitions the US congress chose as benchmarks for poverty assessment tools are somehow questionable. In general, it is a very good and ambitious idea to develop country-wide applicable PATs but, in reviewing our results, we think it is critical that USAID requires its implementation partners to use these poverty assessment tools for their targeting in order to receive funds from USAID. That said, we believe that - at least in diverse countries like Indonesia – the development of regional tools would be more effective at accurately targeting the very poor.

3. Additional remarks on indicator based poverty assessment and the connection to poverty dynamics analysis [10]

The previous chapter focused primarily on the prediction capability of the poverty assessment tools which were developed by myself in 2005 (van Edig, 2006). In this chapter, the results from the re-estimation of the poverty indicators with the 2007 data set are presented. A re-estimation was done to test whether the indicator composition of the tools remain robust over time. To know about this is particularly important to assess the need for re-calibration. All (potential) poverty assessment tools, in terms of indicators and corresponding weights (i.e. coefficients) from 2005 as well as from 2007 can be found in appendices I to VIII.

Additionally, this chapter addresses the question of whether the poverty predictors from Model 2, which I would recommend for targeting in Central Sulawesi, are limited detecting only chronically poor households due to their long-term characteristics.

3.1 Re-estimation of poverty assessment tools for Central Sulawesi

I re-estimated the models using the 2007 data set to observe changes in the indicator composition. I found new sets of indicators and compared them to the indicator sets identified in 2005. The procedure for this re-estimation was identical to the procedure used in 2005. For the variable selection Ordinary Least Squares (OLS) regression models were used. The dependent variable was "predicted daily per capita expenditures". The indicator selection was done using SAS, and applying the MAXR technique. MAXR seeks to maximise the R^2 considering all combinations among pairs of regressors. R^2 is the ratio of the variance in the dependent variable that is explained by the model and its regressors, divided by the overall observed variance of the dependent variable. Its value can range between 0 and 1. A value closer to one indicates a higher percentage of explained variance. In a first step, MAXR tries to find an one-variable model, which provides the highest R^2. In the next step, another variable is added. This variable has to be the one, which yields the greatest improvement in R^2. Then each variable in the model is compared with each variable not in the model. MAXR 'decides' after each comparison, whether to remove a variable in order to

[10] Analysis and results presented here are partly from the paper "How robust are indicator based poverty assessment tools over time? Empirical evidence from Central Sulawesi, Indonesia" by Xenia van Edig, Stefan Schwarze, and Manfred Zeller presented at the IAAE conference 2009 in Beijing, China, URL: http://ageconsearch.umn.edu/handle/51674.

achieve a maximal R^2. This procedure is done until no more maximisation is possible or a certain amount of variables (e.g. 15 as in the case of my poverty assessment tool) is reached. However, an major drawback of this procedure is that sampling weights cannot be included.

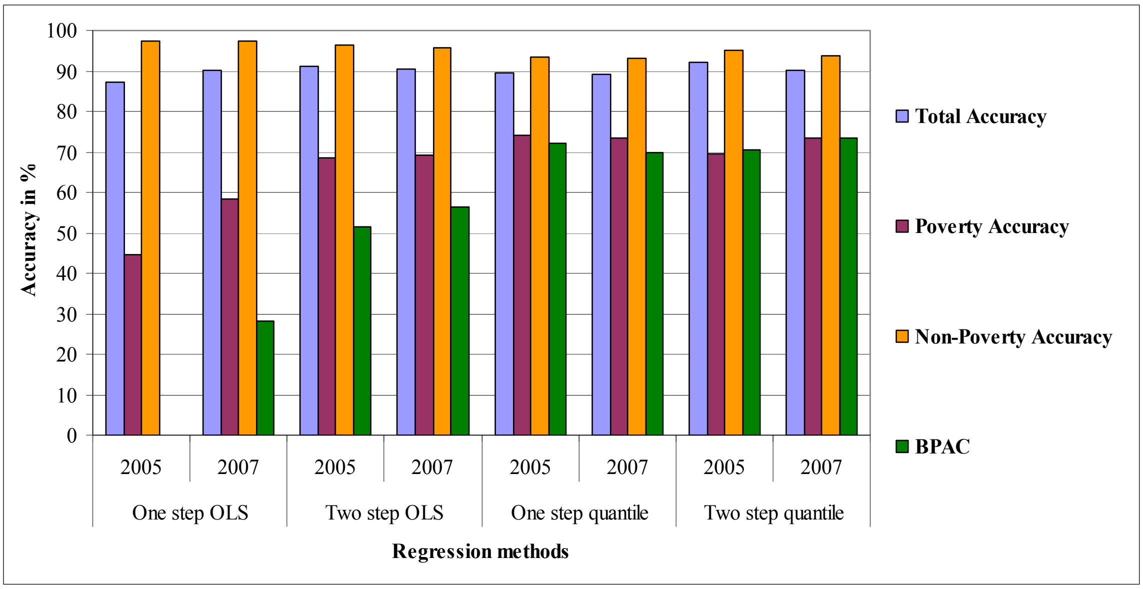
In addition, a number of checks and related adjustments have to be made during the indicator selection. E.g. it had to be checked whether the coefficient carries the sign that concurs with what one would expect from theory. For example the variable 'bed ownership (1=yes)' has to have a positive sign, because richer households are more likely to have beds compared to poorer households. On the opposite the variable 'food expenditure share of total consumption expenditures in percent' has to have a negative sign, because poorer households normally spend a higher share of their total expenditures on food than richer households do (Engel's law). Any of those variable sets found can be described as a poverty assessment tool for the purpose of identifying the poverty status of a household.

As almost 280 indicators were compiled from the composite questionnaire some kind of pre-selection for the indicators entering Model 1 was necessary to guarantee enough degrees of freedom for the model estimation. Thus, all variables were split into seven dimensions, namely 'education', 'food, health and clothing', 'demography and occupation', 'assets and durable goods', 'agricultural assets and land ownership', 'housing' and 'finances, social capital and others'. The best indicators were selected by MAXR out of each dimension. Model 1 works with 86 variables.

Model 2 only allows variables in the model, which are ranked as "easy-to verify" by the Indonesian staff. This were 92 variables. As mentioned above, additionally nine control variables were forced in each model with an INCLUDE statement. These variables were: household size, household size squared, the age of the household head and age of household head squared and five district dummies. In addition to the OLS regressions in SAS, the models were estimated using quantile regressions in STATA to possibly improve the assessment of the expenditures of the poor. In 2007, the variables entering the final models were the same as in 2005. Thus, no further pre-selection of variables was needed.

3.1.1 Re-estimation of Model 1

For the purpose of comparing the accuracy of results for the estimations of Model 1 estimations in 2005 and 2007, two-step quantile regression delivered the best overall accuracy results for both years. In general, the level of accuracy performance was very similar in both years. Only one-step OLS delivered a much higher BPAC in 2007 than in 2005 increasing from 3.7 percent in 2005 to 32.1 percent in 2007. Nonetheless, the accuracy performance of one-step OLS remained low (Figure 5).



Source: own data; N (2005)= 279; N (2007)= 282

Figure 5: Comparison of the estimation accuracy in 2005 and 2007 (Model 1)

Regarding the indicators included in one-step regressions for Model 1, only one of the indicators remained unchanged in 2007 as compared to 2005. This was the "natural logarithm of annualized total consumption from composite questionnaire". Table 8 displays the one-step indicators from both years for comparison.

Table 8: Indicators for one- step regressions in 2005 and 2007 (Model 1)

Indicators 2005	Indicators 2007
Maximal education of any female household member is completed secondary level	Number of children in school age 6-16
Number of days out of the last seven days in which any of four superior foods was eaten (large fish, beef/pork/buffalo meet, chicken/duck or egg)	Household purchases rice monthly (1=yes)
Household ate less food for less than 10 days within the last 12 month (1=yes)	Household members always ate enough of what they wanted (1=yes)
Natural logarithm (LOG) of average clothing expenditures of household members	Household ate less food for more than 10 days within the last 12 month (1=yes)
Household feels that healthcare expenditures are above need (1=yes)	Household head has no education (1=yes)
LOG value of metal cooking pots	Household ate broken rice because of food scarcity (1=yes)
Household agrees that people in the neighborhood are basically honest and can be trusted (1=yes)	Percentage of dependents younger than 15 and older than 64 (in relation to household size)
Household agrees that if it lose a goat or pig some body would help look for it (1=yes)	Bucket ownership (1=yes)
LOG expenditures on other expenditure, social events and leisure in the last 12 month	Family member work some were else and sends money
Total value of received dowry in past three years	Satellite dish ownership(1=yes)
LOG of annual total consumption expenditures from section C	LOG of annual total consumption expenditures from section C
Total value of remittances sent divided by total household expenditures	Number of metal cooking pots owned

Source: own data

Table 8 continued: Indicators for one- step regressions in 2005 and 2007 (Model 1)

Indicators 2005	Indicators 2007
Total value of remittances received divided by total household expenditures	LOG of value of major funds and assets inherited since last survey
Total value of transportation assets	Total size of rooms in the house in m^2
Household made a recent home improvement (1=yes)	Main entrance door has no lock (1=yes)

Source: own data

Both indicator sets for the second step of the two-step models from Model 1 are displayed in Table 9.

Table 9: Indicators for two-step regressions in 2005 and 2007 (Model 1)

Indicators 2005	Indicators 2007
Maximum education of any female household member is: completed secondary level	Number of children in school age 6-16
Household member lost weight because of food scarcity (1=yes)	Household feels that education expenditures are below need (1=yes)
Food expenditure share of total consumption expenditures in percent	Natural logarithm (LOG) of expenditures for education in the last 12 month
Household eats rice mixed with maize because of food scarcity (1=yes)	Household head has no education (1=yes)
Age of youngest household member	Number of household members with completed secondary education
Percentage of dependents younger than 18 and older than 60 (in relation to household size)	Household ate less food for more than 10 days within the last 12 month (1=yes)
Household head works outside of agriculture (1=yes)	In the last 7 days household ate only plain rice with chili (1=yes)
Trunk or suitcase ownership (1=yes)	Household ate broken rice because of food scarcity (1=yes)
Total value of furniture sets owned by household	Household uses cooking fuel other than collected wood (1=yes)

Source: own data

Table 9 continued: Indicators for two-step regressions in 2005 and 2007 (Model 1)

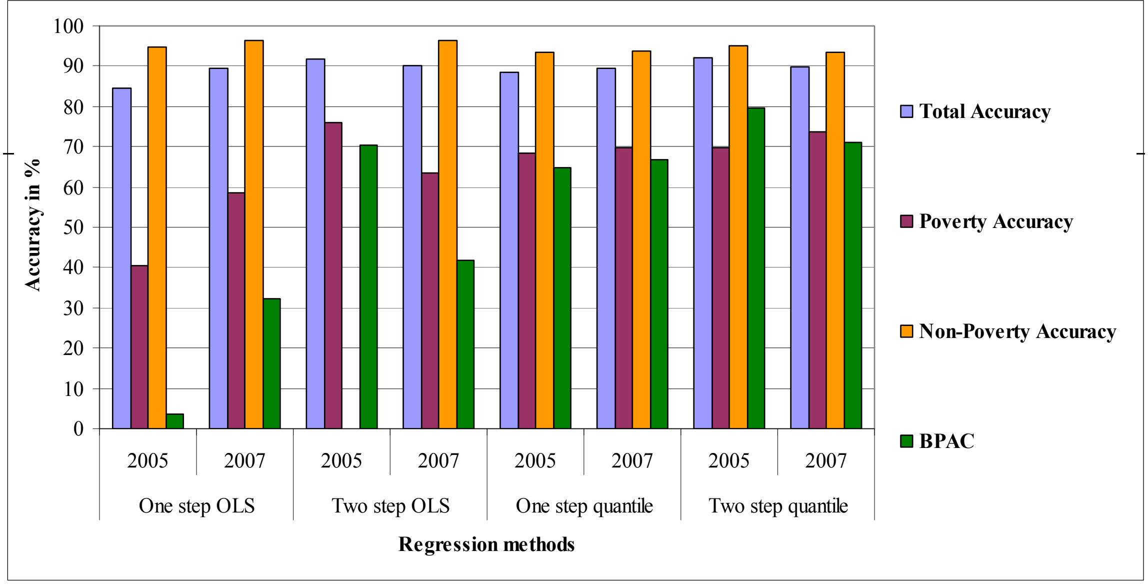
Indicators 2005	Indicators 2007
Household agrees that people in the neighborhood are basically honest and can be trusted (1=yes)	Household head works as wage laborer in agriculture (1=yes)
In the last three years household borrowed money from informal market (1=yes)	LOG of monthly transportation expenditures
LOG of annual total consumption expenditures from section C	Number of beds owned
Total value of transportation assets	LOG of value of major funds and assets inherited since last survey
Household made a recent home improvement (1=yes)	Total number of rooms in the house
Exterior walls are out of brick or stone (1=yes)	Number of organizations any household member participates in

Source: own data

Regarding the indicators included in two-step regressions for Model 1, none of the indicators remained the same in comparison with 2005.

3.1.2 Re-estimation of Model 2

In 2005, one-step quantile regression provided the best accuracy results for Model 2. In 2007, two-step quantile performed somewhat better. In 2005, one-step quantile delivered a BPAC of 72.2%, which slightly decreased slightly to 69.8% in 2007. Two-step quantile showed the opposite: in 2005 the BPAC was 70.4%, and in 2007 it reached 73.6%. The BPAC of one-step OLS for Model 2 also increased from 0% in 2005 to 28.3% in 2007. However, one-step OLS also showed low accuracies.



Source: own data, N (2005)= 279; N (2007)= 282

Figure 6: Comparison of the estimation accuracy in 2005 and 2007 (Model 2)

For one-step regressions of Model 2 the following indicators remained the same in 2007 as in 2005: "total rooms in the dwelling", "cow ownership", "number of trunks and suitcases owned" and "motorcycle ownership" Thus, only four indicators out of 15 indicators were robust over time. A full list of the selected indicators can be found in Table 10.

Table 10: Indicators for one-step regressions in 2005 and 2007 (Model 2)

Indicators 2005	Indicators 2007
Total number of rooms in the house	Total number of rooms in the house
Clock ownership (1=yes)	Bucket ownership (1=yes)
VCD-Recorder ownership (1=yes)	Satellite dish ownership (1=yes)
Motorcycle ownership (1=yes)	Motorcycle ownership (1=yes)
Cow ownership (1=yes)	Cow ownership (1=yes)
Household uses cooking fuel other than collected wood (1=yes)	Household uses cooking fuel other than collected wood (1=yes)
Toilet is personal pit toilet (1=yes)	Number of beds owned
Water from well in residence yard (1=yes)	Main entrance door has no lock (1=yes)

Source: own data

Table 10 continued: Indicators for one-step regressions in 2005 and 2007 (Model 2)

Indicators 2005	**Indicators 2007**
Household head sleeps in bed with thin mattress made of fibers (1=yes)	Exterior walls are brick or stone (1=yes)
Household cooks in separate kitchen (1=yes)	Floor of dwelling is cement with cover (ceramic etc.) (1=yes)
Household has own or shared electricity (including generator) (1=yes)	Total number of females in the household
Percentage of dependents younger than 18 and older than 60 (in relation to household size)	Number of dependents younger than 18 and older than 60
Household made a recent home improvement (1=yes)	Number of metal cooking pots owned
Number of trunks and suitcases owned	Number of trunks and suitcases owned
Metal cooking pots ownership	The size of rooms in m^2

Source: own data

When comparing the indicators from two step regressions in both years, five indicators (a third of all indicators) remained the same: “total rooms in the dwelling”, “bicycle ownership”, “cow ownership” “household head works outside of agriculture” and “household uses other cooking fuel than collected wood”. The indicators for the second step of the two-step regressions are displayed in Table 11.

Table 11: Indicators for two-step regressions in 2005 and 2007 (Model 2)

Indicators 2005	Indicators 2007
Total number of rooms in the house	Total number of rooms in the house
Stove ownership (1=yes)	Number of furniture set owned
Bicycle ownership (1=yes)	Bicycle ownership (1=yes)
Motorcycle ownership (1=yes)	Number of stoves owned
Cow ownership (1=yes)	Cow ownership (1=yes)
Number of chicken owned	Chicken ownership (1=yes)
Lock of main entrance door is padlock (1=yes)	Refrigerator ownership (1=yes)
Exterior walls are brick or stone (1=yes)	Number of bulls owned
Light source: electricity with shared connection (1=yes)	Refrigerator ownership (1=yes)
Household cooks in separate kitchen (1=yes)	Number of metal cooking pots owned
Household head works outside of agriculture (1=yes)	Household head works outside of agriculture (1=yes)
Toilet is shared (pit toilet or improved latrine) (1=yes)	The size of rooms in m^2
Toilet is shared (pit toilet or improved latrine) (1=yes)	The size of rooms in m^2
Ratio of dependents younger than 18 and older than 60 years	Floor of dwelling is earth or bamboo (1=yes)
Household uses cooking fuel other than collected wood (1=yes)	Household uses cooking fuel other than collected wood (1=yes)

Source: own data

3.1.3 Conclusion of model re-estimation

With the analysis described above, I want to show how the indicator composition change when the models (i.e. poverty assessment tools) are re-estimated with a new data set two years after the first calibration. For both re-estimated models, I observed that the level of accuracy was approximately the same in 2005 and 2007. The one exception was that one-step OLS showed much better performance in 2007 than in 2005 for both models. In re-estimating the models, more indicators were repeated for both years in Model 2 than in Model 1. This was largely due to the long-term characteristics of the indicators included in Model 2. One additional reason for the change in indicator composition might also be found in the fact that poverty assessment is not an analysis of the causes of poverty, but rather a prediction of poverty occurrence. Even though indicator composition changed from 2005 to 2007, the indicators included in both models represented similar dimensions of poverty. Therefore, we assume that the new 2007 poverty assessment tool would face weaknesses similar to those that the 2005 tool faced. It appears that a re-calibration of the tools is necessary from time to time. Further research may be needed to better determine the intervals of re-calibration for the PATs.

3.2 Is Model 2 detecting only the chronic poor?

As described in Chapter 2, the majority of the Model 2 indicators are constant or change only very slowly over time. Nevertheless, we suggested the use of Model 2 with one-step quantile coefficients for practitioners use in Central Sulawesi (see previous chapter). The potential problem with this tool is that it may fail to capture short-term poverty dynamics, detecting only the chronic poor, while missing the transitory poor.

Based on this assumption, I tested how well the different poverty assessment tools (from Model 2) function in detecting chronic poverty in contrast to cases of transitory or absent poverty. For this purpose I reapplied the indicators and the corresponding weights (in terms of coefficients) from 2005 to the 2007 data set (as done in Chapter 2).

The categorization into chronic and transitory poor was done following the spells approach. Thus, those households identified as poor in both years are categorized as chronic poor and those households who faced poverty in only one of the survey years are categorized as transitory poor (further description in Chapter 4).

Table 12 displays the accuracy results for all households who participated in both survey years. In summary, the best BPAC (45.17%) was achieved with two-step OLS regression, while the best poverty accuracy was achieved with two-step quantile. As was mentioned previously, for the two-step model it is necessary to calculate the predicted per capita expenditures in two steps. In the first step (here one-step OLS/ one-sep quantile), expenditures for all households are estimated. In the second step, per capita expenditures are re-estimated for those households whose predicted daily per capita expenditures fall below a certain expenditure percentile in the first step of the regression. For the remaining households the predicted expenditures from the first step remain unchanged.

In Tables 13-15 the accuracy results for the different poverty groups are displayed. For the chronic very poor, or those households found to live on less than 1$ US PPP in both years, the best accuracy was achieved by using one-step quantile method: the poverty accuracy achieved 92% and the BPAC 84% (Table 13). Because the 'chronic poor' group consists entirely of those households categorized as absolute poor, there is no non poverty accuracy. As regards the transient poor (Table 14), the one-step quantile method delivered the best BPAC (52.17%), and the best poverty accuracy was achieved with two-step quantile (69.74%). For the estimation of the never poor, one-step OLS was found best suited (Table 15). As the 'never poor' only includes households that are not very poor, it was not possible to calculate poverty accuracy, under coverage, leakage, or BPAC.

Table 12: Accuracy Model 2

	Percentile	Total accuracy (%)	Poverty accuracy (%)	Non-poverty accuracy (%)	Under-coverage (%)	Leakage (%)	Actual head-count (%)	Predicted head-count (%)	PIE[I]	BPAC[II]
1 step OLS		82.58	54.17	88.89	45.83	50	18.2	18.9	0.5	50
2 step OLS	38	82.58	58.33	87.96	41.64	54.17		20.45	2.25	45.17
1 step quantile		78.79	75	79.63	25	91.67		30.3	12.1	8.33
2 step quantile	38	75.38	79.71	74.54	20.83	114.58		35.2	17	-14.04

Source: own data; N=264

Note: [I]Poverty Incidence Error; [II]Balanced Poverty Accuracy Criterion

Table 13: Accuracy Model 2 among the chronic poor

	Percentile	Total accuracy (%)	Poverty accuracy (%)	Non-poverty accuracy (%)	Under-coverage (%)	Leakage (%)	Actual head-count (%)	Predicted head-count (%)	PIE[I]	BPAC[II]
1 step OLS		68	68	-	32	0	100	80	-20	36
2 step OLS	38	80	80	-	20	0		68	-32	60
1 step quantile		92	92	-	8	0		92	-8	84
2 step quantile	38	88	88	-	12	0		88	-12	76

Source: own data, N=25 households

Note: [I]Poverty Incidence Error; [II]Balanced Poverty Accuracy Criterion

Table 14: Accuracy Model 2 among the transitory poor

	Percentile	Total accuracy (%)	Poverty accuracy (%)	Non-poverty accuracy (%)	Under-coverage (%)	Leakage (%)	Actual head-count (%)	Predicted head-count (%)	PIE[I]	BPAC[II]
1 step OLS		55.1	39.13	69.23	60.87	34.78	46.94	34.69	-12.25	13.04
2 step OLS	38	51.02	34.78	65.38	65.22	39.13		34.69	-12.25	8.69
1 step quantile		57.14	56.52	57.69	43.48	47.83		48.98	2.04	52.17
2 step quantile	38	59.18	69.74	50	30.43	56.52		59.18	12.24	43.48

Source: own data, N=49 households

Note: [I]Poverty Incidence Error; [II]Balanced Poverty Accuracy Criterion

Table 15: Accuracy Model 2 among the never poor

	Percentile	Total accuracy (%)	Poverty accuracy (%)	Non-poverty accuracy (%)	Under-coverage (%)	Leakage (%)	Actual head-count (%)	Predicted head-count (%)	PIE[I]	BPAC[II]
1 step OLS		91.58	-	91.58	-	-	0	8.42	8.42	-
2 step OLS	38	91.05	-	91.05	-	-		8.95	8.95	-
1 step quantile		82.63	-	82.63	-	-		17.37	17.37	-
2 step quantile	38	77.83	-	77.83	-	-		22.11	22.11	-

Source: own data, N=190 households

Note: [I]Poverty Incidence Error; [II]Balanced Poverty Accuracy Criterion

The results affirm that the poverty status of the chronically poor households is estimated with a higher accuracy than that of the transitory poor. Looking at the disaggregated results, it seems reasonable to suggest that Model 2 as PAT and as a one-step quantile delivers acceptable results for all categories.

From these findings the question arises how these figures look for Model 1. Model 1, which includes all kinds of indicators, is less likely to favor the chronic poor. In general, I found lower accuracy results applying the tools derived with Model 1 in 2005 to the 2007 data set. For all households, the highest BPAC was 39.58%, generated by applying two-step quantile regressions. For the chronic poor, the highest predicted accuracy was found with one-step quantile, giving a poverty accuracy of 88% and a BPAC of 76%. With regard to the transitory poor, the best BPAC was again achieved with one-step quantile (43.48%). One-step quantile also delivered the highest poverty accuracy (60.87%). The best prediction of never poor households was provided by two-step quantile, which gave a non-poverty accuracy of 90%.

From these findings, I conclude that Model 2 is better suited to predict the chronic poor, as it delivers a poverty accuracy four percent higher than Model 1. The prediction power of both models is less pronounced when it comes to the transitory poor, and Model 1 does not appear to have any major advantages over Model 2 in this regard. Also, Model 2 gives a better prediction of the never poor.

4. Short-term poverty dynamics of rural households in Central Sulawesi, Indonesia – Evidence from panel data of 2005 and 2007

Summary

The temporal component of poverty is an important part in poverty analysis. For the goal of poverty reduction it is important to know whether poverty is chronic or transitory, because appropriate poverty reduction strategies differ. Insurances or income stabilization programs are particularly suited to the protection of transient poor from idiosyncratic shocks. In contrast, the direct transfer of income or assets could help the chronic poor. For potential poverty reduction projects in Central Sulawesi, a rather poor province in Indonesia, it is important to know whether they are dealing with chronic or transitory poor. Therefore, we want to find out about poverty dynamics in the region and the determining characteristics of chronic and transitorily poor households.

The data for the study was collected in 13 villages in the vicinity of Lore Lindu National Park in rural Central Sulawesi, Indonesia. In 2005 and 2007, the same 264 randomly selected households participated in the survey. We calculated the Foster-Greer-Thorbecke (FGT) poverty measures as well as the Sen and Sen-Shorrocks-Thon Index to draw a general picture of the poverty situation in both survey years. Regarding the 1$ US poverty line, the situation in the study area slightly improved; the headcount index declined insignificantly from 19.3% in 2005 to 18.2% in 2007. However, we observed an increasing number of people living on less than 2$ US PPP. In 2005, 47 percent of the population felt short of this threshold. In 2007, this had increased to 59.1 percent. Furthermore, we created a transition matrix including both international poverty lines (1 and 2$ US) to show the movement into and out of poverty. Additionally, we identified the intensity of chronic or transitory poverty. Multi-nominal logit regression analyses was conducted to trace underlying determinants of chronic and transitory poverty. We found that a lack of non-farm employment opportunities and low endowment of social capital are major poverty determinants. These results are used to draw policy conclusions with respect to the alleviation of transitory and chronic poverty in Central Sulawesi.

4.1 Introduction

Poverty reduction is a main goal of development policies, programs and projects (e.g. Zeller et al. 2001, Aho et al. 1998, United Nations 2009). To achieve this target it is important to not only identify the poor but also determine whether the poverty is chronic or transitory, as the appropriate poverty reduction strategies will differ (Grootaert et al. 1995, Jalan and Ravaillion 2000, Hulme and Shepherd 2003, McKay and Lawson 2003). This important temporal component of poverty was described as dynamic poverty by Baulch and Hoddinott (2000).

Only a minority of the household surveys conducted in the 1990s are suitable for the analysis of poverty dynamics as most surveys were lacking appropriate panel modules (McKay and Lawson 2003). Systematic efforts in the analysis of short and long-term poverty dynamics were undertaken since the year 2000 (Dercon and Shapiro 2007). Even though an increasing number of panel data sets are available for developing countries there are still big gaps in the analysis of poverty dynamics. This might be because appropriate panel modules for the analysis of poverty are lacking or that no data is available for certain regions (McKay and Lawson 2003).

To characterize the situation regarding poverty development in Indonesia during the last 15 years, it has to be mentioned that in mid-1997, Indonesia, like other Asian countries, faced a severe financial crisis which led to economic distortions. Within this crisis, the national headcount poverty rate increased quickly increasing from 15.6% in 1996 to 27.4% in 1999 (Suryahadi and Sumarto 2003). After the crisis, poverty decreased when the economic situation stabilized. Therefore, many households only faced short-term poverty during the crisis. Thus, poverty sometimes seems to be a 'fluid condition', due to transitions into and out of poverty (Widyanti et al. 2001). The 1997 economic crisis drew attention back to the issue of poverty reduction in Indonesia (Sumarto et al. 2004). However, after poverty rates in Indonesia came down to the pre-economic crisis level in 2005, the situation worsened again after 2006 due to rising food prices (World Bank 2008). Therefore, even when the overall economic situation stabilizes, poverty is still prone to fluctuations.

For Indonesia the studies of SMERU research institute on poverty dynamics (Suryahardi and Sumarto 2001, Widyanti et al. 2001) used SUSENAS cross-sectional household surveys for their analysis. In another approach, Alisjahbana and Yusuf (2003) used panel data of the Indonesian Family Life Survey (IFLS) from 1993 and

1997. However, it was pre-crisis data they used and therefore drawing relevant policy implications from their analysis might be difficult. A more recent attempt to analyze poverty dynamics in Indonesia was undertaken by Widyanti et al. (2009). They used the IFLS data from 1993, 1997 an 2000. These data sets were also used in the empirical analysis of 'pathways out of poverty' by McCulloch et al. (2007) and Weisbrod (2008). Thus, our study adds the most recent panel data from 2005 and 2007 to the analysis of poverty dynamics in Indonesia.

According to Baulch and Hoddinott (2000), three dimensions in the analysis of poverty dynamics have to be considered: the welfare measure, the time frame over which the welfare metric is measured, and the method for summarizing these measures over the population of interest. In our study, the daily per capita consumption expenditures serve as a welfare metric. They were compared with the international poverty lines of 1 and 2$ PPP and to the national poverty line (for the development of the poverty lines from 2005 to 2007 see appendix IX). We use a panel data set from two years (2005 and 2007) comprising a sample of 264 randomly selected households. The sample is regarded as representative for the research area (compare section 4.2). Thus, our data only cover one region in Indonesia: the area in the vicinity of Lore Lindu National Park in Central Sulawesi. While the region is located on one of the five biggest islands in Indonesia, it remains a remote area.

This study adds substantially to an understanding of the determinates of poverty mobility in the Indonesian context, providing an in-depth analysis of a small region using recent panel data. Specifically, it addresses the following questions:

1. How did the poverty situation in the vicinity of the Lore Lindu National Park changed between 2005 and 2007?
2. How dynamic is poverty in the research area?
3. What are determinants of chronic/ transient poverty?

The paper is organized as follows. After describing the sampling method and data collection conducted in Central Sulawesi, the methods used for the data analysis are presented. The first step of the data analysis is the calculation of a set of poverty measures on the basis of three alternative poverty lines. Then the movement into and out of poverty between 2005 and 2007 is examined. The framework used to select the household characteristics for the regression analysis is presented. After the result section, conclusions are drawn and policy implications are provided.

4.2 Sampling method and data collection

The data was collected in 13 villages in the vicinity of the Lore Lindu National Park in rural Central Sulawesi, Indonesia[11]. For the selection of the villages and the households, a stratified random sampling method was chosen (for a description of the sampling procedure see Zeller et al. 2002). Because the stratified random sampling was applied, we included weights in the data analysis as far as the statistical packages were supporting them. As mentioned earlier, household data from two expenditure surveys (2005 and 2007) were used for the same 264 randomly selected households. Furthermore, we conducted both surveys at the same time of the year to reduce the influence of the seasonal dimension on transient poverty.

Like other panel studies, our sample had to face drop-outs of respondents and therefore, the validity of the results was threatened by attrition biases. Attrition might be caused by households which move away or because some households refuse to participate in a second survey round. Attrition matters for analytical purposes because the households that remain in the panel are liable to be systematically different from those that dropped out (McKay and Lawson 2003). In our case the attrition rate as comparatively low: from 279 households in 2005 to 264 households in 2007. For the 15 households which dropped out between 2005 and 2007, we found that the differences between the expenditures of this group and of those who remained in the sample was very low, i.e. that the expenditures were allocated across the entire range of the 2005 expenditures. Thus a distortion of the results by attrition bias is unlikely.

Two questionnaires were used in both surveys. On the one hand, we used a benchmark questionnaire to obtain the daily per capita consumption expenditures of each household. This part resembled the consumption module of the *Living Standard Measurement Survey* (LSMS) of the World Bank and essentially had the same purpose of collecting descriptive information about poverty and monitoring it over time (Grosh and Glewwe 2000). With LSMS, only monetary poverty is measured, which is defined as a shortfall of consumption/income from a poverty line. The underlying assumption is that "uniform monetary metrics account for all heterogeneity across individuals and their situations" (Ruggeri Laderchi et al. 2003, p. 247). It is argued that welfare can be measured as total consumption enjoyed if utility maximizing behavior is assumed.

[11] The research was part of a collaborative research center on the Stability of Rainforest Margins (STORMA), which was funded by the Deutsche Forschungsgemeinschaft (DFG) and launched in 2000. The research center was jointly undertaken by the universities of Göttingen and Kassel (both in Germany), and Universitas Tadulako and IPB Bogor (both in Indonesia).

However, this widely used approach is criticized as it does not account for the multidimensionality of poverty such as Sen definition if poverty as deprivation in his capability approach (1999).

To account for the multidimensionality of poverty, we used a composite questionnaire to derive indicators of poverty in dimensions other than expenditures such as health, education, housing or assets.

4.3 Methods for data analysis

4.3.1 Descriptive Analysis

In the following sections, the different methods used in our descriptive analysis are described. As a first step, the different poverty measures used are presented and the relevance of poverty line choice. We explain how the transition matrix is constructed. We define the terms chronic, transient and never poor and explain the problem of measurement error.

4.3.1.1 Poverty measures

We calculated the Foster-Greer-Thorbecke (FGT) poverty measures – the poverty headcount, poverty gap ratio and the squared poverty gap ratio - as well as the Sen- and Sen-Shorrocks-Thon Index to draw a broad picture of the poverty situation in the region in both years. More information on these measures can be found in Sen 1976, Foster et al. 1984, Ravallion 1992, Shorrocks 1995, Ebert and Moyes 2000, Xu and Osberg 2001, Aguirregabiria 2006, and Haughton and Khandker 2009.

The *headcount index* P_0 is the most widely used poverty measure. It only accounts for the proportion of a population that is regarded as poor. It does not tell anything about the severity of poverty or the distribution of poverty among the poor. P_0 is given as

$$(6)\ P_0 = \frac{N_p}{N} ,$$

where N_P is the number of poor in a population N, i.e. the proportion of poor of the total population.

The *poverty gap ratio* P_1 assesses the depth or severity of poverty. Sometimes it is seen as the minimum cost for poverty elimination by showing how much transfer to the poor would be necessary to lift their incomes/expenditures up to the poverty line (assuming perfect targeting). The mean proportionate poverty gap across the entire population, with zero gap for the non-poor, P_1 is given as

$$(7)\ \mathrm{P}_1 = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_1}{z}\right],$$

where z is the poverty line and y is the consumption of the poor, arranged in ascending order.

The *squared poverty gap ratio* is a weighted sum of poverty gaps, i.e. the mean squared proportionate poverty gap. With the squared poverty gap (P_2), conclusions about the distribution of poverty among the poor (whether it is equal distributed or not) can be made. P_1 is given as

$$(8)\ \mathrm{P}_2 = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{z-y_1}{z}\right]^2 .$$

The *Sen Index* integrates the number of poor, the depth of their poverty and the distribution of poverty among the poor. In contrast to the FGT poverty measures, the Sen-Index is not decomposable to different subgroups. P_S is given as

$$(9)\ P_s = P_0(1-(1-G^P)\frac{\mu^P}{z}),$$

where P_0 is the headcount, μ^p is the mean income/expenditure of the poor and G^p is the Gini-coefficient among the poor (a measure of the income [in our case expenditure] distribution ranging between 0 and 1).

The *Sen-Shorrocks-Thon-Index* (SST) is a modified version of the Sen-Index an it is normalized to take values between zero and one. A value equal to zero indicates that all incomes are above the poverty line while an unit value of one indicates the extreme case where all the individuals are poor with an income of zero. P_{SST} is given as

$$(10)\qquad P_{SST} = P_0 P_1^P(1+\hat{G}^P),$$

where P_0 is the headcount, P_1^P the poverty gap ratio among the poor and $\hat{G}^p$ the Gini coefficient of the poverty gaps of all households.

It is possible to decompose the SST index into a form providing information on the sources of changes of poverty over time. This is given as

$$(11)\qquad \Delta\ln P_{SST} = \Delta\ln P_0 + \Delta\ln P_1^P + \Delta\ln\hat{G}^P,$$

where the differences of the natural logarithms of the single components are summed.

4.3.1.2 Does the choice of poverty lines matter?

The choice of the poverty line might matter a great deal for policy decisions (Ravallion 1998). A poverty line set at a low income or expenditure level might lead to different findings than a poverty line set at a higher level. Therefore, varying the poverty line can be used to examine the sensitivity of the poverty rates to different poverty lines (Haughton and Khandker 2009). Testing for stochastic dominance of any order, i.e. testing whether one distribution is dominating another over time or space, is a further step in this analysis. It can be determined whether poverty is greater in one distribution or another for general classes of indices and for ranges of poverty lines (Davidson and Duclos 2000).

As result, we conducted first and second order stochastic dominance tests to assess the influence of different poverty lines. Formally, in testing for first order stochastic dominance an income/expenditure distributions, y_1 is compared with another income/expenditure distribution, y_2. First order stochastic dominance of y_1 is given when the cumulative distribution of y_1 lies nowhere above and somewhere below the cumulative distribution function of y_2. To do so, the headcount poverty rate on the y-axis is plotted against consumption expenditures ranging from 0 to any maximum on the x-axis. The curve derived is a cumulative distribution function and is called a *poverty incidence curve*. If none of the poverty deficit curves dominates the other, one might check for second order stochastic dominance by calculating the area under the poverty incidence curve, i.e. under each point, and plotting this against the poverty line. Doing so, a *poverty deficit curve* is derived. Consequently, the poverty deficit curve can be drawn by displaying the total values of poverty gaps on the y-axis and the consumption expenditures on the x-axis. If the sum of the total poverty gaps – the poverty deficit – is nowhere above and somewhere below the other, we find second order stochastic dominance (Haughton and Khandker 2009). With this analysis, one is able to say whether poverty has risen or fallen over time no matter which poverty line is applied.

4.3.1.3 Poverty mobility: the chronic, the transient and the never poor

To display the movement into and out of poverty, we created a transition matrix including both poverty lines (1 and 2$). The more consistent over time the income/ expenditure estimates given by a household just above and just below the poverty line in the first panel year, the more robust be the conclusions regarding poverty mobility drawn from a poverty mobility or transition matrix (Scott 2000).

Furthermore, we identified how many households are chronically poor, transitory poor, or never poor. The most important issue about chronic poverty is its extended duration (McKay and Lawson 2003).

As mentioned before, our survey comprises a time period of only two years. Our results, as well as the results of several other studies (see Table 22), suggest that statements on transient poverty can be made and trends regarding chronic poverty can be observed. This in spite of the assertion by Hulme and Shepherd that a chronic poor household has an extended duration of poverty of at least five years (2003). They argue that five years is perceived as a significant period of time in most societies. They state that poverty lasting a time period of five years often indicates lifetime poverty and if so, poverty often is passed on to subsequent generations (for an analysis of intergenerational poverty persistence in Indonesia see Pakpahan et al. 2009.) Furthermore, they name practical reasons such that panel surveys often have five years intervals of data collection.

Using the spells approach, the poor are characterized as either chronic poor, i.e. those who remained (very) poor in both years of the panel or transitory poor, i.e. those who were poor in either one of the survey years (McKay and Lawson 2003). Dercon and Shapiro (2007) describe the same idea as poverty persistence, i.e. the proportion of the households that is always, sometimes, or never poor across the survey waves. Thus, the spells approach focus on the transition into and out of poverty. With this approach, it is likely to overestimate the transient poor due to a measurement error (Hulme and Shepherd 2003). Further discussion on the measurement error and how we dealt with it can be found in section in 4.3.1.3.

Another possibility to deal with the analysis of poverty dynamics is the so called components approach. The components approach attempts to isolate the underlying components of poverty from transition shifts. This is measured either by the average income/consumption over a period of time or by a prediction of income based on known household characteristics (Hulme and Shepherd 2003). With the components approach, those that are unlikely to escape poverty over a longer period should be identified according to their characteristics. The components approach does not refer to the concept of persistent poverty: The important issue in considering a household chronic poor is that a permanent component of living standard falls short of the poverty line (McKay and Lawson 2003). For example Jalan and Ravaillon (2000) employed a components approach. They defined transient poverty as “the contribution of consumption variability over time to the expected consumption poverty” (p. 83). Thus chronic poverty is defined as the non-transient component, i.e. the “poverty which remains when inter-temporal variability in consumption has been smoothed out (…)”. For the components approach at least three repeated observations are needed (Baulch and Hoddinott 2000). Making this approach not applicable to our data set.

The spells approach as well as the components approach might be sensitive to the level at which the poverty line is set (Mc Kay and Lawson 2003). That is mainly why in our analysis we refer to both international poverty lines of 1 and 2$ US.

4.3.1.4 Measurement error

As Baulch and Hoddinott (2000) point out, it is crucial that studies on poverty dynamics account for measurement error. This is particularly important as the results for poverty categories can be biased in short-term analysis. It might seem that households move into and out of poverty even if their poverty status actually remains the same. This is especially true for those households with expenditures close to the poverty line. Thus it is clear that the measurement error in the income (expenditure) variable might affect the extent of mobility. How it actually affects mobility is less clear: on the one hand, it will depend on the accuracy with which a household reports its income/expenditures over time. On the other hand, it depends on how the measurement error varies among households with different income/consumption levels at any point in time (Scott 2000). Nevertheless, due to measurement error in the welfare measure it is likely that the degree of poverty mobility is overstated (Dercon and Shapiro 2007).

Primarily, two kinds of measurement error occur if expenditures are taken as a welfare indicator: on the one hand, there might be intrinsic difficulties in measuring the variables and on the other hand, problems arise when recall-related data is used and values for home production are imputed (Baulch and Hoddinott 2000). Additionally, the interview situation might be different because the household (or individual) was interviewed before in the same context, i.e. in the second (or third) survey round of a panel the household might respond differently compared to the first round. Thus the data quality might improve or degrade between two interviews (McKay and Lawson 2003). Another problem mentioned by Dercon and Shapiro (2007) is that price deflation over time and space reflects real price changes only inaccurately. As the case if survey responses differ from the true expenditures, the deflation of prices can increase the variance of the welfare measure without actually increasing the variance in welfare. Baulch and Hoddinott (2002, p. 8) conclude: "(…) if we assume there are some genuine poverty transitions, we would still expect measurement error to reduce the number of households who are regarded as 'always poor' or 'never poor' and increase the number of those regarded as 'sometimes poor'." Dercon and Shapiro (2007) note that rotating panels and short panels particularly suffer from difficult differentiation of poverty fluctuation and measurement error from genuine mobility. The latter they define as either the movement of people into a persistently better standard of living or the fall into the persistent state of poverty.

But how should one treat this problem? There are two possible responses to address the measurement error. One can either quantify the magnitude of measurement error or try to eliminate it. Dercon and Shapiro (2007) cited several studies which used instrumental variables (iv) or pseudo-panel approaches to deal with the problem. The background of using iv to account for the measurement error they summarize as follows: "If the instrument predicts true consumption but error in measuring the instrument is uncorrelated with error in measuring consumption, then the instrument can give reliable inference on mobility" (p. 96). The problem with this method is that the correlation of instrument and consumption might be rather weak and that the error in measuring the instrument might be correlated with the error in measuring consumption.

McKay and Lawson (2003) also refer to the two possibilities of treating the measurement error mentioned above. They describe one way to assess the effect of measurement error by comparing income with consumption based standards. Consumption tends to be a better measure of the living standard and is generally considered to be more accurately measured. Therefore consumption tends to have a lower variance than income. Given that the choice of welfare measure has an impact on the extent of poverty mobility the authors employ a sensitivity analysis on the chosen measure. As to the adjustment of the measurement error, McKay and Lawson (2003) cite the study of McCulloch and Baulch (2000) who constructed a model which allow them to calculated the measurement error using both consumption and income data. For their analysis on poverty mobility they used an adjusted income variable. Bhatta and Sharma (2006) employed a similar approach to correct their consumption measure.

However, we think when consumption expenditures are taken as welfare measures the comparison with the rather weaker measure of income would be misleading.

Another approach was employed by Breen and Moisio (2004). They used latent class models to correct the error in headcount measures in the analysis of poverty dynamics in several EU member states. This approach is not suitable in our case as the Markov chains they refer to require more than just two points in time.

In our analysis, we refer to the approach of Alderman and Garcia (1993). They conducted a theoretical analysis on the extent of measurement error and regressed the changes in assets (which can be assumed to be well measured) on the changes in expenditures. With their method they tried to quantify the amount of the variance due to measurement error. From this, Baulch and Hoddinott (2000) conclude that "if the measured changes in incomes were nothing more than the measurement error, then there should be no relation between asset changes and income changes" (p. 8). Keeping this interpretation in mind, our results suggest that there was true variance between our observations in 2005 and 2007, as the change in household size, the change in the value of transportation assets owned, and the change in the size of irrigated rice fields owned were significant in a first difference regression on the change in the daily per capita expenditures (see appendix X). Based on this analysis, we conclude that the observed changes in the daily per capita expenditures are related to true changes and not due to measurement error.

To observe further whether the variance in our data is true, or due to measurement error, we conducted additional analysis – following Scott (2000) - on the process of impoverishment of six households whose status changed from being non poor (>2$ US) in 2005 to being very poor (< 1$ US) in 2007.

4.3.2 Regression analysis

Poverty dynamics often are modeled by assessing the risk of a household or an individual to remain poor for a given period of time (Justino and Lichtfield 2003). However, given that we only have available two time periods, we are interested in the question of which factors determine chronic and transient poverty. The categories "chronic" and "transitory" indicate a certain "status" of poverty, but not the expenditures themselves. Thus poverty outcome can take three distinct values: chronic poor, transient poor, and never poor. Therefore, it is advisable to use a discrete choice model. The main criticism of using “qualitative” discrete variables (as the poverty status) instead “quantitative“ continuous variables (as expenditures) is that information gets lost (Ravaillon 1996, Deaton 1997).

Notwithstanding the possibility of using ordered logit or probit models, we choose a multinomial logit model (MNL). In general, MNL are used to model processes that involve a single ‘decision’ among several alternatives that can not be ordered (Justino and Lichfield 2003). Although, there is, strictly speaking, no choice between the movements into and out of poverty, several alternatives can be differentiated regarding the poverty status. Thus we applied MNL because “although poverty status is based on an underlying welfare measure (per capita expenditure) defined on an interval scale, it is not always appropriate to assume that chronic poverty represents a higher level of deprivation than transient poverty, as would be implied by treating it as an ordinal variable” (Bhatta and Sharma 2006, p.11). It is hence reasonable to treat the poverty status as a nominal variable and to use a multinomial logit model to trace factors influencing the movement into and out of poverty. Baulch and McCulloch (2002) tested ordered probit as well as multinomial logit models. The authors state the MNL enables the identification of characteristics which are more prevalent within each category. In an earlier publication, McCulldoch and Baulch (1999) found the ordered logit approach suitable for understanding the relative influence of different household characteristics on its poverty status, while they found the multinomial logit approach enables the identification of the characteristics that are more prevalent within each category.

There are several other studies that also use multinomial logit regression to identify key drivers, interrupters and maintainers of poverty dynamics. For example, Glewwe et al. (1999) and Justino and Lichtfeld (2003) use this approach for Vietnam, Lawson et al. (2006) use it for Uganda and Baulch and McCulloch (2002) use it for Pakistan.

In our MNL, the dependent variables take the values 0 for never poor households, 1 for households which were poor in one of the two periods and 2 for households which were poor in both observation periods. To account for multidimensionality either the integration of qualitative research methods or the integration of non-monetary variables in the quantitative analysis is needed (Hulme and Shepherd 2003). In our approach, we refer to the latter of these strategies. For analyzing different household characteristics that might influence whether a household is trapped in chronic poverty or not, we refer to the sustainable livelihoods framework. As described in section 3.2.1, the independent variables were selected following the livelihood pentagon. They should reflect the household's livelihood situation as well its ability in coping with shocks.

Since we are interested in which initial household characteristics affect the evolution of the poverty status over time, the values of the independent variables are those from the initial year 2005.

In the model, P_{ij} is the probability that a household i is in a particular poverty status j. It is modeled as a function of the independent variables X_i:

$$(12) \qquad P_{ij} = \frac{e^{x'_i ß_j}}{1 + \sum_{k=1}^{2} e^{x'_i ß_k}} \text{ for } j\text{=0,1,2,}$$

where $ß_j$ is a vector of the coefficients, $ß_0$ is set to zero, and j can take the values 0 (non-poor), 1 (transient poor) and 2 (chronically poor). The non-poor category (j= 0) serves as base category for the regression.

4.3.2.1 Selection of explanatory variables (potential determinants)

Hulme and Shepherd (2003) point out, the analysis of purely "money-metric" expenditure data might not be sufficient, as multi-dimensional deprivation is more likely. Most studies on poverty dynamics use either income ore expenditures as a measure of welfare. One reason to focus on these "money-metrics" is that they can fluctuate most over even short time periods (McKay and Lawson 2003). Dercon and Shapiro (2007) claim the importance of causal analysis as well as of the setting a household or individual lives in. They give the example that it is a common finding that education helps people escape poverty, but rarely analysis is done to determine this is really the effect of education itself or the result of that families that are able to offer other possibilities when they are able to offer education.

As mentioned above, the explanatory variables were selected according to the sustainable livelihoods framework. The sustainable livelihoods framework itself strives to help researchers and policymakers view objectives, scopes and priorities of the development from the perspective of the poor (Carney 2003). It is a people-centered, participatory, multi-level, sustainable and dynamic approach (Ashley and Carney 1999). As its use is committed to poverty alleviation it can be seen as an analytical guideline based on a normative principle (Carney 2003). The sustainable livelihoods framework shows linkages, interactions and feedbacks between transforming institutional structures and processes and household vulnerability, as well as the influence of these transformations on livelihood strategies, and thus livelihood outcomes. These livelihood outcomes impact the asset endowment of a household.

A household lives under several given settings related to its locality: the natural environment can be described as the physical setting; the community of residence in provides the social setting; and which rules are valid in the society and how these rules are set forms the legal and political setting. To access the economic behavior of households the economic setting, i.e. policies that affect the returns to assets and their variability, is very important (Baulch and Hoddinott 2000).

The sustainable livelihoods framework refers to the endowments with livelihood assets a household or individual has within these settings. These assets are summarized in the sustainable livelihood pentagon. For a comprehensive analysis of poverty dynamics it is important to understand the asset endowment of the households or as Ashley and Carney (1999) put it, one needs to know how poor people construct their lives.

The assets can be categorized respective the livelihood pentagonas described in Adato and Meinzen-Dick 2002:

Natural Capital: land water, forests/ marine resources, air quality, erosion, protection, biodiversity

Physical Capital: transportation, roads, buildings, shelter, water supply, sanitation, technologies, communications

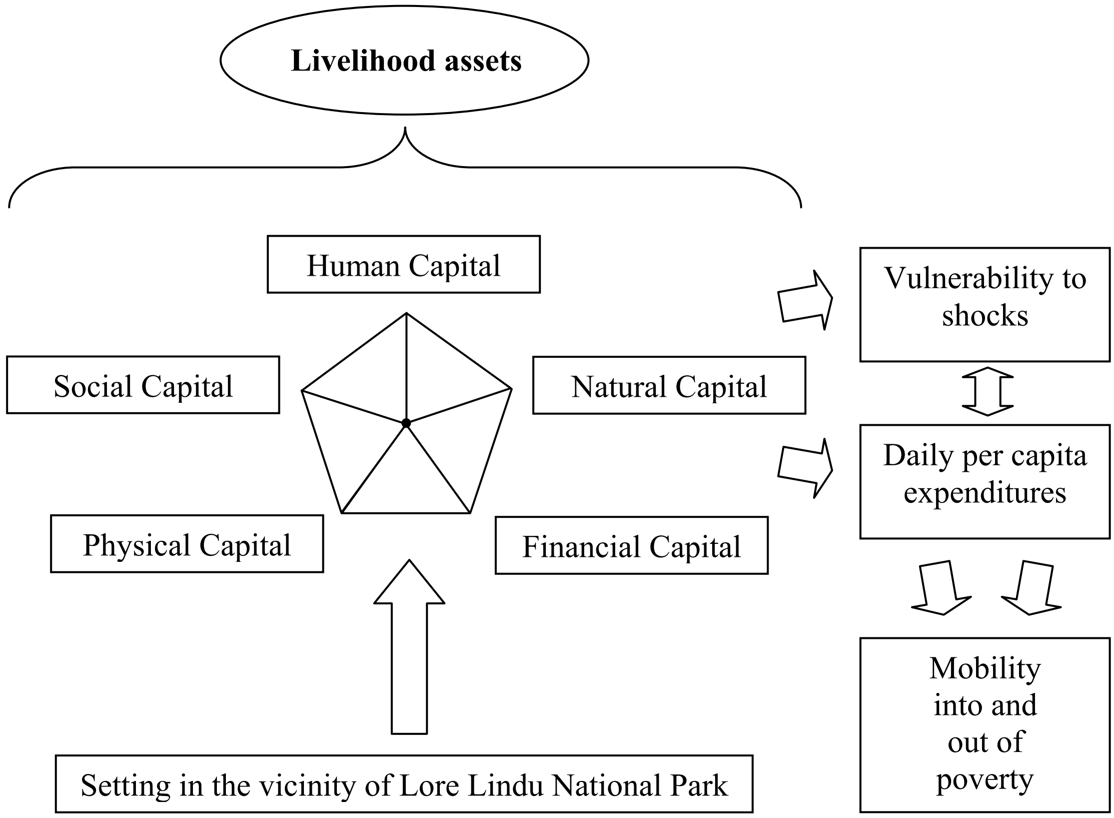
Financial Capital: savings, credits, inflows

Human Capital: education, skills, knowledge, health, nutrition, labor power

Social Capital: trust-increasing networks, ability to work together, access to opportunities, informal safety nets, membership in organizations.

Commonly, the sustainable livelihoods framework is used by several organizations to analyze the causes of poverty (Adato and Meinzen-Dick 2002). In our work, we want to use its core – the livelihood assets - to analyze the determinants of poverty mobility. As mentioned above, the use of these assets is affected by policies, institutions and processes. As the time frame of our research is only two years and all households live in the same vicinity, we expect all households to be affected in a similar way. Thus we exclude political parameters from our analysis and concentrate on the household assets endowment.

Our conceptual framework is constructed as follows: All households analyzed live around the Lore Lindu National Park, they face similar environmental and political conditions. However, their endowment with livelihood assets, i.e. human, social, physical, and financial capital, might be very different. This asset endowment is the basis for the income a household earns and can further influences its vulnerability to shocks. Both low incomes/expenditures and the vulnerability to shocks influence poverty mobility (Figure 7).



Source: own construction

Figure 7: Conceptual framework for the selection of independent variables

From the composite questionnaire, we included those variables in the analysis which fit into the framework (for a list of the variables selected see Table 23). These variables served as independent variables which might help to explain the determinants of poverty mobility. It is, however, sometimes difficult to differentiate between the causes of poverty and its outcomes. For example, (very) poor people might be less mobile due to lacking transportation assets, and this might foster their poverty. On the other hand, because of their poverty, they cannot afford to buy those assets. Other examples of variables that might face an endogeneity problem are “non agriculture income”, “access to credit" and "former household members sending remittances", because the actual outcome of these variables is highly influenced by the household's decision-making in the past. One way to circumvent endogeneity is the use of instrumental variables (iv). The pre-condition to reduce endogeneity with iv are suitable instruments which are correlated with the explanatory variable but not with its error term (Deaton 1997). However, our problem of endogeneity is more related to simultaneity. Thus, one or more of the explanatory variables is jointly determined with the dependent variable (Wooldrige 2003). One way to treat this problem is the estimation of so called simultaneous equation models. The underlying assumption of these models is that each equation has its own *ceteris paribus*, causal interpretation. Therefore it does not make sense to estimate simultaneous equations which are determined by the same set of variables and represent the behavior of the same economic agent (e.g. household), as neither equation can stand on its own, for example housing expenditures and saving (Wooldrige 2003) or in our case remittances and expenditures.

We can state that we don't have appropriate instruments for all included explanatory variables and thus a complete identification of iv is not possible. Further we cannot refer to simultaneous equation model because our variables do not fulfil the underlying assumptions. Therefore, we use lagged variables to assess the causes of poverty dynamics. With lagged variables one ensures that the right hand side variables are prior time to the left hand side variable (Deaton 1997). However, the potential problem remains that if a omitted "third" variable affects y today and x yesterday, the today y will contain information that is correlated with yesterdays x, and therefore not avoid endogeneity as supposed (Deaton 1997).

Of course not only specific household characteristics lead to chronic and transitory poverty. Often shocks have a major impact on the household's well-being. Shocks can be either idiosyncratic (if they are restricted only to a single household) or covariate (if they affect all households in a certain locality) (Baulch and Hoddinott 2000). To control for the influence of covariate shocks as well as for the influence of agro-ecological differences, we included regional dummies in our analysis (see Alderman and Garcia 1993).

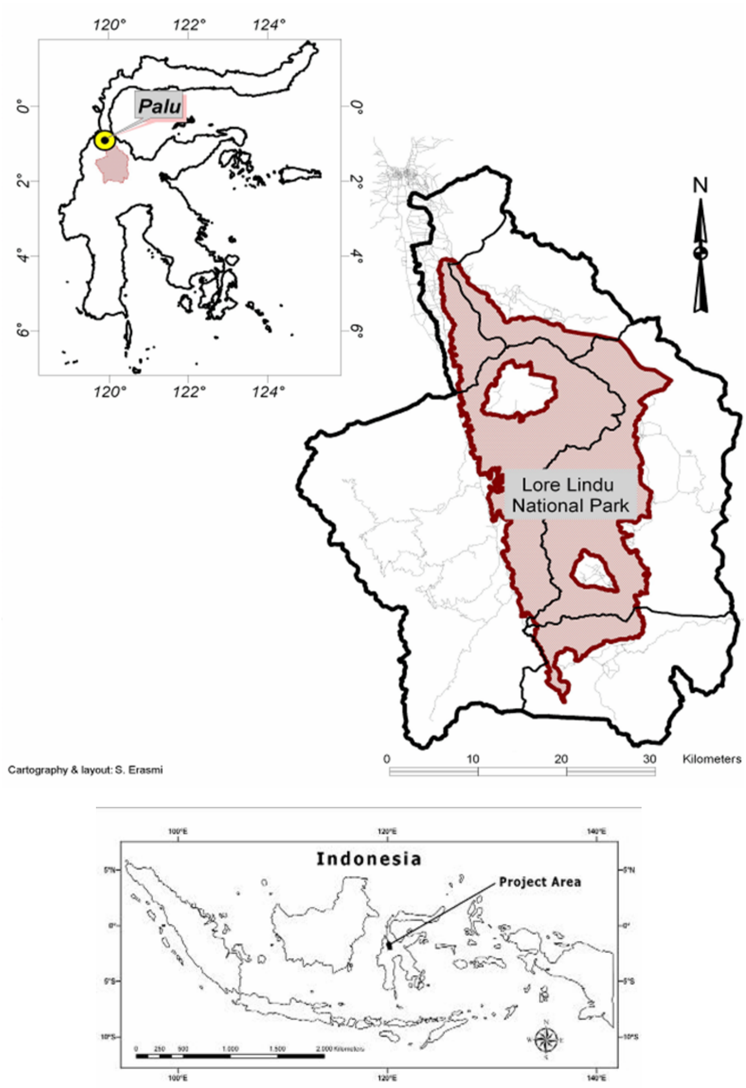
4.4 Results and discussion

4.4.1 Descriptive statistics

In section 4.4.1, the results of the different parts of our descriptive analysis (compare section 4.4.3) are displayed.

4.4.1.1 Research area

The research area is located in the vicinity of the Lore Lindu National Park in Central Sulawesi (Figure 8).



Source: Erasmi (2004)/ STORMA project

Figure 8: Research area

It covers about 7100 km^2 and is inhabited by 132,000 people (Maertens et al. 2002). In the research area, most households are farm households and most of the household heads are self-employed in agriculture. The percentage of household heads working as agricultural wage laborers is very low and it dropped from 7.6 percent in 2005 to 3.8 percent in 2007. The percentage of household heads working in the non-agricultural sector slightly went up from 8.3 percent in 2005 to 12.9 percent in 2007. The average area possessed by a household slightly increased from 2.02 hectares in 2005 to 2.16 hectares in 2007. Predominately paddy, cocoa, coconuts and vegetables are grown, and some households also own livestock. While the percentage of households owning big animals such as bulls, cows or pigs went down from 2005 to 2007 (e.g. cow ownership from 14.8 percent to 10.2 percent), the percentage of households owning small animals such as chicken increased from 45.1 percent in 2005 to 56.4 percent in 2007.

As to the demographic situation, most of the households are male-headed. The percentage of female-headed households slightly increased from 7.6 percent in 2005 to 10.6 percent in 2007. About 20 percent of the households in our sample are migrants.

4.4.1.2 Changes in different poverty measures

The choice of poverty measures and poverty lines is always somewhat arbitrary (Haughton and Khandker 2009). Therefore we want to present five different poverty measures, namely the Foster-Greer-Thorbecke (FGT) poverty measures, the Sen-Index, and the Sen-Shorrocks-Thon Index for both survey years. These measures and indices are displayed for the national poverty line and for the international poverty lines of 1 and 2$ PPP (Table 16). Any differences in the means of the FGT poverty measures between both years was tested using a paired t-test.

Table 16: Different poverty measures for three poverty lines from 2005 and 2007

Poverty measure/ indicies	International poverty line of 1$ US in PPP		Indonesian national poverty line for rural areas		International poverty line of 2$ US in PPP	
	2005	**2007**	**2005**	**2007**	**2005**	**2007**
Headcount Index (P0) in %	19.3	18.2	34.9	37.5	47	59.1
Poverty Gap (P1) in %	4.1	4.3	11.1	11.9	19.6	22.4
Poverty Gap Squared (P2)*100	1.3	1.5	4.7	4.9	10	11
Sen Index *100	5.6	5.9	14.7	15.6	24.9	29.4
SST[I] Index *100	7.7	8.1	19.6	20.7	32.5	35.7

Source: own data, N=264 households

Note: [I]Sen-Shorocks-Thon

Table 16 shows that the headcount poverty rate using the 1$ US poverty line slightly decreased from 2005 to 2007. However, this change was found to be insignificant. The depth of poverty and the inequality among the poor increased slightly 2007. The integrated indexes also increased. To summarize, severe poverty hardly declined within two years, but the situation of the very poor worsened slightly. As mentioned earlier, an interesting index for the analysis of causes of poverty development is the Sen-Shorrocks-Thon- Index (see Table 17 and 18)

As to the national poverty line the situation is different: The headcount index increased by 2.65 percentage points, the poverty gap and the poverty gap squared slightly increased (Table 16). However these changes are statistically insignificant. In addition, both integrated indexes, the Sen and SST index increased.

We observe the most tremendous change when looking at the households below the 2$ US poverty line in both years. The increase in the headcount poverty rate was quite large. Between 2005 and 2007, the poverty incidence grew by 12.1 percent (Table 16). This change was statistically significant at the 1 percent level. Furthermore, the depth of poverty became larger; the mean poverty gap increased by 2.5 percent. These increasing poverty gaps were found to be statistically significant, but at the 5 percent level. Additionally, income became less equally-distributed within the group of the poor: the squared poverty gap grew by 1 percent. That results follows the earlier mentioned findings from the World Bank (2008). It could be that the increase in prices of certain commodities affected the poor more than the very poor due to the type of commodity (such as meat or non food items (e.g. for personal care).

For both international poverty lines, we analyzed the different sources of poverty changes over time using the decomposed SST index. The decomposed form of the SST index can provide evidence on which factor - poverty incidence, poverty severity or inequality among the poor – was most influential for the changes in poverty (Haughton and Khandker 2009). In the decomposition matrix, the values of the components included in the SST index as well as the difference of the natural logarithm of these components are displayed (compare section 3.1.1).

Table 17: Decomposition of SST Index, 1$ US poverty line as reference

	SST	**P_0**	**P_1^P**	**$1+\hat{G}^p$**	**Δ ln SST**	**Δ ln P_0**	**Δ ln P^P_1**	**Δ ln(1+$\hat{G}^p$)**
2005	0.077	0.193	0.211	1.881				
2007	0.081	0.182	0.236	1.888	0.05	-0.06	0.11	0.004

Source: own data, N=264

Notes: SST: Sen-Shorocks-Thon Index; Δ ln SST: difference of natural logarithm of SST (2005/2007); P_0: Headcount Index; Δ ln P_0: difference of natural logarithm of P_0 (2005/2007); P_1^P: Poverty gap ratio among the poor Δ ln P_1^p: difference of natural logarithm of P_0 (2005/2007); $\hat{G}^p$: Gini coefficient among the poor ; Δ ln $\hat{G}^p$: difference of natural logarithm of P_0 (2005/2007)

Regarding the 1$ US poverty line, the natural logarithm of the poverty gap among the poor (Δ $P^P{}_1$) increased (Table 17). Therefore, more money would have to be transferred to the very poor to lift them up to a consumption level equal to the poverty line. The inequality among the very poor, here measured by the Gini coefficient among the poverty gaps ($\hat{G}^p$), increased only a little.

Table 18: Decomposition of SST Index, 2$ US poverty line as reference

	SST	P0	P1P	1+Ĝp	Δ ln SST	Δ ln P0	Δ ln PP1	Δ ln(1+Ĝp)
2005	0.325	0.47	0.418	1.656				
2007	0.357	0.591	0.38	1.593	0.09	0.23	-0.1	-0.04

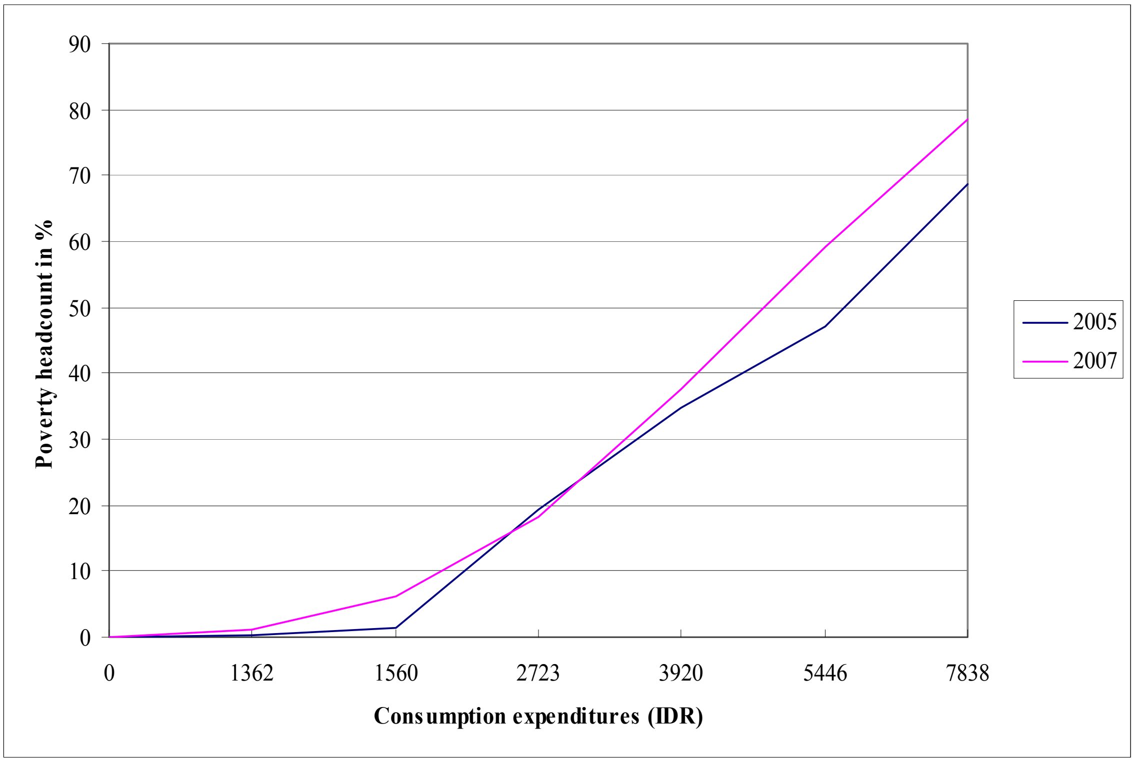
Source: own data, N= 264

Notes: SST: Sen-Shorocks-Thon Index; Δ ln SST: difference of natural logarithm of SST (2005/2007); P_0: Headcount Index; Δ ln P_0: difference of natural logarithm of P_0 (2005/2007); P_1^P: Poverty gap ratio among the poor Δ ln P_1^p: difference of natural logarithm of P_0 (2005/2007); $\hat{G}^p$: Gini coefficient among the poor ; Δ ln $\hat{G}^p$: difference of natural logarithm of P_0 (2005/2007)

Regarding the second threshold presented in this manner, mainly an increasing poverty incidence let to a change in the SST index, her visible from Δ ln P_0 (Table 18). The poverty gap among the poor as well as the Gini coefficient among the poverty gaps even declined slightly, as we can see from the decrease in Δ ln P^P_1 and Δ ln (1+$\hat{G}^p$).

4.4.1.3 Influence of poverty lines

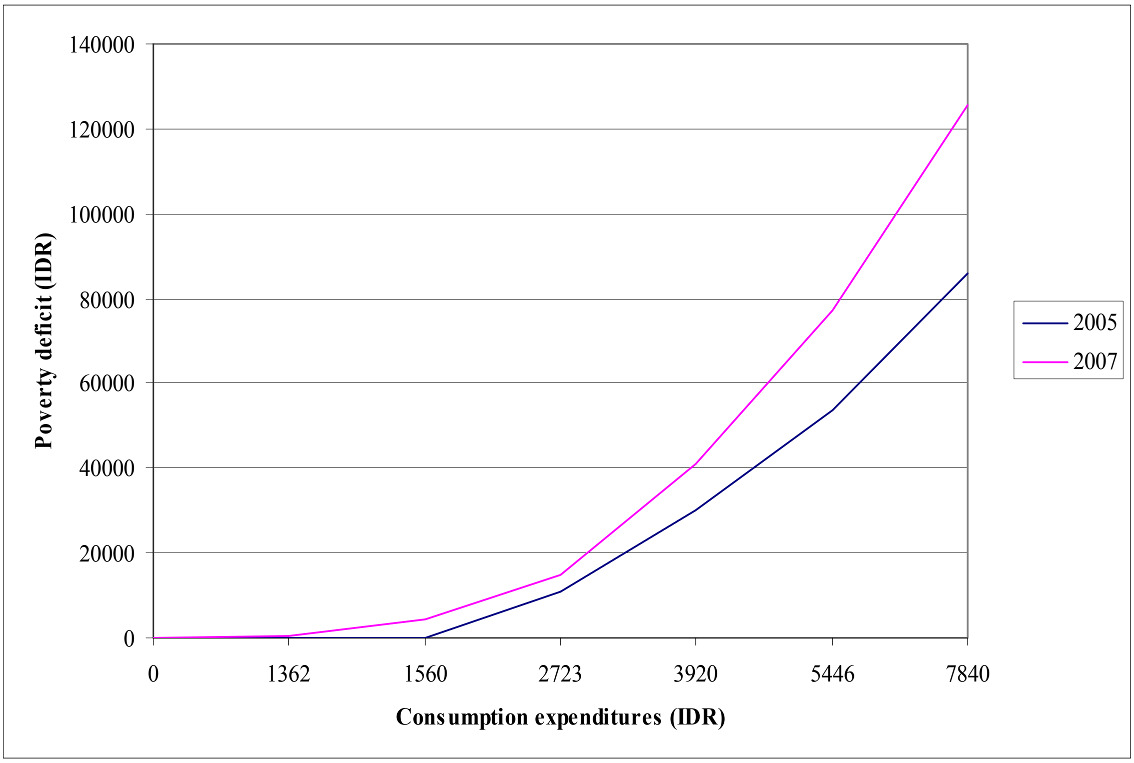
As it was mentioned before we assessed first and second order stochastic dominance to test for the influence of the poverty line choice. We find no first order stochastic dominance in the poverty incidence curve. Thus from the poverty incidence curve no conclusion whether poverty had fallen or risen between 2005 and 2007 was possible (Figure 9).



Source: own data; N= 264

Figure 9: Poverty incidence curves - testing for first order stochastic dominance

Therefore, we tested for second order stochastic dominance by drawing poverty deficit curves for both years (Figure 10). As this graph illustrates, the poverty deficit curve for 2007 is entirely to the left of the 2005 curve indicating that the poverty deficit was always greater in 2007, no matter which poverty line was used. Thus we can state that poverty in the region increased.



Source: own data; N= 264

Figure 10: Poverty deficit curves – testing for second order stochastic dominance

4.4.1.4 Transition matrix

Up to this point, the change of poverty over time was discussed using aggregate measures constructed from cross-sectional data. However, such analysis fails to show the movement into and out of poverty among a given group of households. In Table 19, the movement of Central Sulawesi households into and out of poverty is summarized in a transition matrix. In the transition matrix, the absolute numbers of households in the different poverty groups in both years are displayed. Furthermore, the percentages for the corresponding years are displayed (row percent relates to the year 2005 and column percent relates to the year 2007).

Table 19: Transition matrix on 1 and 2$ US PPP poverty line from 2005 - 2007

2005	2007			
	Very poor* (Row %)	**Poor** (Row %)**	**Non poor (Row %)**	**Total (Row %)**
Very poor* (Column %)	25 (52.1) (49)	17 (15.7) (33.3)	9 (8.3) (17.7)	51 (19.3) (100)
Poor (Column %)**	17 (35.4) (23.3)	36 (33.3) (49.3)	20 (18.5) (27.4)	73 (27.7) (100)
Non poor (Column %)	6 (12.5) (4.3)	55 (50.9) (39.3)	79 (56.4) (29.9)	140 (53) (100)
Total (Column %)	48 (100) (18.2)	108 (100) (40.9)	108 (100) (40.9)	264 (100) (100)

Source: own data; N=264 households

Notes: *refers to the 1$ poverty line, ** refers here to those living between 1 and 2$ US

A total of 49 percent of the households who lived on less than 1$ US in PPP in 2005 remained very poor in 2007. In 2007, 33.3 percent of the households who were very poor in 2005 were able to shift from being very poor to being poor (< 2$ US). Together with the 17.7 percent of the very poor who raised their expenditures to more than 2 $US purchasing power parities (PPP) they can be described as escapee households.

Contrary to this movement out of extreme poverty, about 23 percent of the households who were classified as poor in 2005 were classified as very poor in 2007. Together with the 4.3% of the households considered non-poor in 2005 which had to face extreme poverty in 2007 they can be described as descending households.

Almost half of the households remained poor (live on less than 2 $ US PPP, but on more than 1$ US PPP). Almost two thirds of the non-poor households maintained daily per capita consumption of more than 2 $ in both years.

We further examined the six households who became extremely impoverished over the period, to analyze the process of their pauperization (see also appendix XI). To cross check whether this pauperization really occurred, we compared their ability to serve luxury foods in the week prior to the interview in both years, as a proxy of their transitory expenditures. We found that in four out of six cases, the amount of meals with eggs, meat or fish declined. We also looked at changes in the number of livestock owned, as households are likely to sell livestock to cope with idiosyncratic shocks. None of the households owned big livestock such as bulls, cows and pigs in both years. As to chicken ownership, two households invested in chicken production. In one case the ownership increased from four to 60 chickens and in the other from one to 32 chickens. Both of these households also invested in land and we used the land ownership as a proxy for the household's wealth status. Three households lost land between 2005 and 2007; in two cases they lost 0.5 ha and in one case, they lost 0.25 ha. For one household the situation remained unclear as no land possession was reported in 2005 even though it was reported that the household head works self-employed in agriculture and in 2007, 0.75 ha of land area was reported.

The results might be interpreted twofold: One can argue that these three households who lost land might have had to sell it because of idiosyncratic shocks, such as severe illness of the main income earning person. Two of these households additionally had a higher dependency ratio from children under 15 years and elderly people over 64 years in relation to household size in 2007 than in 2005. The third household head had to change his occupation from self-employed in agriculture to casual worker in agriculture which could indicate a severe occurrence as illness. Because these three household had to sell their major productive asset (land) it is likely that more time would be needed to escape poverty again.

As to the other two households, the investments in farm land and chicken production might have been quite high and therefore consumption smoothing is not possible. Nevertheless it is likely that they could soon escape poverty again as the return to their investments increases.

For the household, whose land ownership situation remained unclear as described before, we only can state that the dependency ratio in the household increased.

Unfortunately, our survey does not include information about negative idiosyncratic shocks such as illness or death. Crosschecking with data from a household survey on income we conducted several months prior to the expenditure survey, we saw no evidence for negative idiosyncratic shocks in these six households. In the expenditure survey, we obtained information about a positive shock of marriage of a first degree relative of the household head. Apparently between 2005 and 2007, none of the six severe impoverished households reported such a costly ceremony.

For comparison, the figures found by Alisjahbana and Yusuf (2003) for all of Indonesia (using the IFLS household survey from 1993 and 1997) are displayed in Table 20. This Table summarizes urban and rural poverty in 13 Indonesian provinces. As a welfare measure they used monthly per capita expenditure and as threshold they used the national poverty lines for the corresponding years provided by the Indonesian Central Body of Statistics (BPS). In the figures from 1997, the influence of the economic crisis is already visible as the headcount increased.

Table 20: Transition matrix for Indonesia from 1993-1997

1993	**1997**		
	Poor	**Non-poor**	**Total**
Poor	7.8%	7.4%	15.2%
Non-poor	11.6%	73.2%	84.8%
Total	19.4%	80.6%	100%

Source: adapted from Alisjahbana and Yusuf (2003)

Even though, a direct comparison of our data with the figures of Alisjahbana and Yusuf (2003) is not possible, we can state that, if we refer only to the two categories of very poor and not very poor (the movement between very poor and non- very poor in this case) is quite similar. Almost half of the households remained very poor in both years, and the other half escaped extreme poverty. In their sample, 13.7 percent of the non-poor households fell into poverty in the second year and for our sample 16.3 percent fell into poverty.

4.4.1.5 Chronic, transitory and never poor

As our data-set comprises only two repeated observations, we use the spells approach (compare to section 4.3.1.2) which defines the *chronic poor* as those who experience spells of poverty in each observation (McKay and Lawson 2003). Therefore, those households whose daily per capita consumption expenditures felt short of the respective poverty line in 2005 and 2007, we defined as the *chronic poor*. The *transitorily poor* were found to be (very) poor in one of both survey years. Those who had consumption expenditures above the poverty line in both years were considered as *never poor*.

For Central Sulawesi, the absolute number of households as well as the percentages for the different categories are listed in Table 21.

Table 21: Chronic, transitory and never poor against the two international poverty lines

Poverty status	1$ US poverty line	2$ US poverty line
Chronic poor	25 (9.5%)	90 (34.%)
Transitory poor	49 (18.5%)	95 (36%)
Never poor	190 (72%)	79 (30%)
Total	264 (100%)	264 (100%)

Source: own data, N=264 households

In many studies, the share of transient poor is higher than the rate chronic poor (Baulch and Hoddinott 2000). In the case of Central Sulawesi, this also is true regarding the 1$ US poverty line: only 9.5 percent of the sample households were in chronic poverty, but 18.5 percent were are transitorily poor. The opposite is the case regarding those who fell short of the 2$ US poverty line. Here, 36 percent of the households were regarded as chronic poor and only 34 percent of the sample was transitorily poor.

Even if the percentage of chronically very poor was comparatively low the movement into and out of poverty is rather dynamic. Therefore, it is worthwhile to analyze the asset endowment of these households.

In general, a comparison of different studies on poverty mobility is difficult, because they might differ in the number of waves, the sample size, the geographic coverage, the welfare measure and the poverty lines used (Mc Kay and Lawson 2003, Dercon and Shapiro 2007). So far, most studies focused on collection of household information rather than tracking individuals. Visits were repeated every three to five years and the panels only consisted of few rounds (McKay and Lawson 2003). This issue might be important as Dercon and Shapiro (2007) state that with an increasing number of rounds, the likelihood that a household will be classified as transient poor increases. There is also evidence for this tendency from Indonesian data. While Alisjahbana and Yusuf (2003) used the IFLS data sets from 1993 and 1997, Widyanti et al. (2009) also took the data-set of 2000 into account. They found 4.2 percent of the households were chronically (always) poor, 9.9 percent as twice poor, 20.2 percent once poor (for a total of 30.1 percent transient poor) and 65.7 percent were never poor using regional poverty lines. The figures concerning transient poor are greater than the figures reported by Alisjahbana and Yusuf (2003) (compare Table 20).

In Table 22, the findings of different surveys on poverty dynamics in several countries are presented (using two repeated observations, applying the spells approach and using consumption expenditures as welfare indicator). Nevertheless, these results should not be compared as no information about the poverty lines used is available.

Table 22: Percent of households chronic, transitory, and never poor from six surveys

Source (cited in Baulch and Hoddinott 2002)	Study location	Number of observations in panel	Study dates	Welfare measure	Percent of households		
					Chronic poor	Transitory poor	Never poor
Carter (1999)	South Africa	2	1993-1998	Expenditure per capita	22.7	31.5	45.8
Dercon and Krishnan (1999)	Ethiopia	2	1994-1995	Expenditure per capita	24.8	30.1	45.1
Grootaert and Kanbur (1995)	Côte d'Ivoire	2	1985-1986	Expenditure per capita	14.5	20.2	65.3
Grootaert and Kanbur (1995)	Côte d'Ivoire	2	1986-1987	Expenditure per capita	13.0	22.9	64.1
Grootaert and Kanbur (1995)	Côte d'Ivoire	2	1987-1988	Expenditure per capita	25.0	22	53.0
Skoufias, Suryahadi and Sumarto (2000)	Indonesia	2	1997-1998	Expenditure per capita	8.6	19.8	71.6

Source: adapted from Baulch and Hoddinott (2002)

4.4.2 Determinants of chronic and transitory poverty

As mentioned, we applied multinomial regressions to identify determinants of chronic and transitory poverty. We conducted this analysis regarding both international poverty lines of 1$ US (Model 1) and 2$ US (Model 2). We chose the category never (very) poor as the base outcome, because we are interested in the factors which influence a deviation from this status (into chronic or transitory poverty). The estimated sets of coefficients represent the effect of the explanatory variables on chronic and transitory poverty relative to the base outcome.

Recall that this study works with the sustainable livelihoods framework for the selection of the explanatory variables. Therefore, they are grouped according to this framework. Additionally, we included sub-district dummies in order to control for agro-ecological differences in the region and thus the natural capital. Our analysis is based on the household characteristics in the base year 2005.

Instead of displaying the regression coefficients, the relative risk ratio (RRR), i.e. the exponentiated coefficients, is denoted.

Suppose

$$(13) \qquad P(y_i = j) = p_{ij} \,,$$

where P is the probability that a household i is in a poverty status j.

As everything in a multinomial logit is stated relative to a base category (here 0),

$$(14) \qquad \frac{p_{ij}}{p_{i0}} = \exp(x_{ij}\beta_j) \,,$$

where p_{i0} is the probability of j=0 (in our case never poor), is the 'relative risk' to the base category. The exponentiated coefficient in multinomial logit is the ratio of two relative risks (the one given x_{ij}+1 to the one given x_{ij}).

$$(15) \qquad \frac{p_{ij}'}{p_{i0}'} = \exp((x_{ij} + 1)\beta_j) \text{ such that}$$

$$(16) \qquad \exp\,(\beta_j) = \frac{\dfrac{p_{ij}'}{p_{ij}'}}{\dfrac{p_{ij}}{p_{i0}}}$$

is the relative risk ration RRR.

This relative risk ratio tells us how the probability of choosing *j* relative to 0 changes if we increase x by one unit (Gutierrez 2005, Bockmann 2009).

In our context it shows how the probability of being transient or chronic (very) poor relative to being never poor changes if the explanatory variable increases by one unit. If the RRR is greater than 1, the probability of becoming part of the transient/chronic poor increases. If RRR is less than 1, it decreases.

Applying MNL, the assumption of the independence of irrelevant alternatives (IIA), i.e. that the inclusion or exclusion of categories does not affect the probabilities associated with the regressors in the remaining categories, has to be satisfied. To test whether this assumption is valid for our data, we applied the suest (seemingly unrelated estimations) command of the Stata 10 statistical software package. Doing so, the IIA was found to be satisfied, i.e. no significant differences in the coefficients were observed.

Table 23 presents the multi-nominal logit regression results for the determinant of chronic and transitory poverty.

Table 23: Determinates of chronic and transitory poverty regarding two poverty lines

Explanatory variables (from 2005)	Reference 1$ US poverty line				Reference 2$ US poverty line			
	Transient very poor		Chronic very poor		Transient poor		Chronic poor	
	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value
Demographics								
Age of household head	1.151811	1.26	1.028005	0.19	1.141301	1.26	1.08235	0.77
Age of household head squared	0.9985987	-1.30	0.9999599	-0.03	0.9988538	-1.10	0.9993779	-0.62
Household is female headed (1=yes)	1.205646	0.27	2.174862	0.54	0.4572629	-1.03	0.196811	-2.11**
Household size	1.613862	3.25***	2.104111	3.85***	1.021331	0.16	1.751724	3.43***
Dependency ratio of members < 15 years and > 64 years and in relation to household size	1.023085	1.89*	1.061391	2.76***	1.022322	1.94*	1.03623	3.08***
Total land area owned by the household in are	0.9984094	-0.91	0.9997533	-0.16	0.999786	-0.24	0.9992881	-0.59

Source: own data, N= 264

Notes: [I]RRR: Relative Risk Ratio; Note: to test statistical differences paired t-test was used; *significant at the 10 percent leve; l**significant at the 5 percent level; ***significant at the 1 percent level,; a) Base category is completed primary education/ uncompleted secondary education; b) Base category is self-employed in agriculture; c) Base category is sub district Sigi Biromaru

Table 23 continued: Determinates of chronic and transitory poverty regarding two poverty lines

Explanatory variables (from 2005)	Reference 1$ US poverty line				Reference 2$ US poverty line			
	Transient very poor		Chronic very poor		Transient poor		Chronic poor	
	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value
Social capital								
Number of organizations the household is member of	0.9320898	-0.76	0.7431445	-1.95*	0.8880719	-1.38	0.9178868	-0.88
Financial Capital								
Household borrowed money from informal market in past three years (1=yes)	0.5057755	-0.98	2.32-19	-29.01***	0.2941469	-2.05**	0.083939	-3.25***
Relative is working elsewhere and sends remittances	0.2135749	-1.44	7.70e-19	-30.47***	0.2556581	-1.65*	0.0149103	-3.09***

Source: own data, N= 264

Notes: [I]RRR: Relative Risk Ratio; Note: to test statistical differences paired t-test was used; *significant at the 10 percent leve; l**significant at the 5 percent level; ***significant at the 1 percent level,; a) Base category is completed primary education/ uncompleted secondary education; b) Base category is self-employed in agriculture; c) Base category is sub district Sigi Biromaru

Table 23 continued: Determinates of chronic and transitory poverty regarding two poverty lines

Explanatory variables (from 2005)	Reference 1$ US poverty line				Reference 2$ US poverty line			
	Transient very poor		Chronic very poor		Transient very poor		Chronic very poor	
	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value	RRR[I]	z-value
Human Capital								
Household head has less than completed primary education (1=yes)[a)]	1.299328	0.43	2.226862	1.33	1.519163	0.79	1.042452	0.07
Household head has higher (secondary or superior)education (1=yes)[a)]	1.127653	0.20	0.9185094	-0.06	3.43853	2.33**	0.651561	-0.63
Household head works outside of agriculture (1=yes)[b)]	0.04885	-2.10**	1.72-19	-37.25***	0.306837	-1.34	0.3988599	-0.91
Household head is wage laborer in agriculture(1=yes)[b)]	2.88915	1.38	2.62-18	-38.24***	1.701534	0.59	1.327691	0.28
Household head is domestic worker or unemployed(1=yes)[b)]	2.045853	0.70	3.136363	0.76	1.526796	0.45	0.626195	-0.45

Source: own data, N= 264

Notes: [I]RRR: Relative Risk Ratio; Note: to test statistical differences paired t-test was used; *significant at the 10 percent leve; l**significant at the 5 percent level; ***significant at the 1 percent level,; a) Base category is completed primary education/ uncompleted secondary education; b) Base category is self-employed in agriculture; c) Base category is sub district Sigi Biromaru

Table 23 continued: Determinates of chronic and transitory poverty regarding two poverty lines

	Reference 1$ US poverty line				Reference 2$ US poverty line			
Explanatory variables (from 2005)	**Transient very poor**		**Chronic very poor**		**Transient very poor**		**Chronic very poor**	
	RRR[I]	**z-value**	**RRR[I]**	**z-value**	**RRR[I]**	**z-value**	**RRR[I]**	**z-value**
District Dummies								
Lore Utara [c)]	1.284358	0.37	4.274678	1.66*	0.9980054	-0.00	0.2649254	-1.73*
Palolo c)	0.35628	-1.25	0.8655451	-0.08	0.5767305	-0.90	0.5565949	-0.92
Kulawi (including village Lawe) [c)]	2.871552	1.60	5.761038	1.81*	2.918002	1.43	1.982703	0.83
Number of observation	264				264			
Wald Chi2 (38)	15691.54				132.58			
Prob > Chi2	0.0000				0.0000			
Pseudo R2	0.3793				0.3873			
Correctly predicted (%)	73.9				59.5			

Source: own data, N= 264

Notes: [I]RRR: Relative Risk Ratio; Note: to test statistical differences paired t-test was used; *significant at the 10 percent leve; l**significant at the 5 percent level; ***significant at the 1 percent level,; a) Base category is completed primary education/ uncompleted secondary education; b) Base category is self-employed in agriculture; c) Base category is sub district Sigi Biromaru

We did not find a significant impact for the age of the household head as a determinant for transient and chronic poverty. Nevertheless, older household heads tend to be more likely to head transient (very) poor households. Comparing our results to the findings of Alisjahbana and Yusuf (2003), who also applied a MNL to a data set of rural Indonesian households, they found a significant positive effect of the age of household head in determining chronic poverty. Regarding the squared age of household head, we observe an inverse U-shape relation ship for all poverty categories. Thus, the probability of being poor is increasing up to a certain point, and decreasing afterwards. However, this finding is not statistically significant.

The probability of becoming chronically poor increases significantly if a household is female-headed. However, this is only the case for the chronic poor, but not for the chronic very poor. Overall, the incidence of female-headed households is low (7.6 percent in 2005). That female-headed households are more likely to face chronic poverty concurs with what often is stated in theory. However, Suryahadi and Sumarto (2003) found in their study on chronic and transient poverty in Indonesia before and after the economic crisis of 1997, there were no significant impact of gender the poverty status. Widyanti et al. (2009), in their study on the relationship between chronic poverty and household dynamics in Indonesia even found that households with a single female without children have the lowest probability of becoming chronic poor, whereas single males with children suffer the highest probability.

We found the household size is a major determinant for all types of poverty, except the transient poor. This finding is supported by the work of Widyanti et al (2009). They also a larger household increases the probability of being chronically poor. This makes sense, in that a higher dependency ratio postulates poverty. The dependency ratioin our case is measured as the number household members younger than 15 and older than 64 (as a ratio to household size). Here, the influence of lifecycle effects becomes visible. This seems to be particularly relevant for chronic poverty. Again, the findings of Alisjahbana and Yusuf (2003) regarding the presence of dependents in a household concur with our finding; higher numbers of small children and elderly people increase the likelihood of poverty, especially chronic poverty.

Furthermore, the available of electricity reduces the likelihood of severe transient and chronic poverty. However, for the transient poor this does not play a role. In the research area, over 70 percent of the households have electricity available. The lack of transportation assets (we used motorcycle ownership as proxy) is common for all kinds of poverty. The relationship between the RRR (here the degree of likelihood to become chronically very poor) and not owning a motorcycle is very high. The size of land owned (considered a major productive asset) was not a significant precondition for being poorer or wealthier. Nevertheless, owning smaller areas of land tend to lead to poverty.

The lack of social capital (number of organizations a to which a household belongs) is especially an issue for the chronically very poor. The probability of becoming poor increases if the household is not a member of any organization. This concurs with finding from Gertler et al. (2006) who estimate the effect of social capital on the ability of households to insure consumption after unexpected negative shocks (also in Indonesia, using the IFLS panel from 1993 and 1997). They found that "(h)ouseholds that are member in many groups in 1997 have lower declines in consumption when health declines between 1993 and 1997 (…)" (p. 477).

In general, there are hardly any formal institutions providing credit in the research area with the households depending mainly on traditional money lenders (Nuryartono 2005). Participation in informal credit markets between 2002 and 2005 reduces the likelihood of being poor. Only the transient very poor are not significantly affected. We cannot compare our results, as all Indonesian studies cited did not include analysis on credit participation.

A very distinct determinant of chronic (severe) poverty seems to be a lack of remittances sent from relatives working elsewhere. Remittances are a crucial income source. On average they account for 16 percent of the daily per capita expenditures.

Even though our education dummies for lower education (completion of less than primary education) and higher education (completion of secondary education or higher) are in most cases not significant, we do not want to understate the importance of education. Low education particularly increases the probability of becoming poor. With higher education we confusingly get significant results suggesting that higher education increases transitory poverty. A possible explanation might be that households who invest in higher education temporary lose part of their labor force. As to education, Suryahadi and Sumarto (2003) found that the economic crisis (serving as a major covariate shock) increased chronic poverty and this was most pronounced for low-educated households.

Our results further suggest that non-agricultural employment reduces the probability for households to fall into, and to be trapped in, poverty. Additionally, agricultural wage labor reduces the likelihood of severe chronic poverty.

Unfortunately, Central Sulawesi was not included in the analysis of Alisjahbana and Yusuf (2003). However, their results suggest that the location of a household in South Sulawesi (integrated as regional dummy in their model), the neighboring province, increased the probability of poverty significantly.

Our model is relatively successful in predicting poverty status. As to the 1$ US poverty line it predicts 74 percent of the households correctly, almost as much as the model of Alisjahbana and Yusuf (2003) which correctly predicted 78 percent of households. Even though the performance regarding the 2$ US poverty line is weaker (60 percent), it still performs better than the model of Lawson et al. (2006) with this model only achieving correct prediction of 51%.

4.5 Conclusion and policy implications

In our analysis we draw a broad picture of the poverty situation in rural Central Sulawesi in the years 2005 and 2007.

We can state that more people faced poverty in 2007 compared to 2005. This finding is supported in two ways. First, the headcount poverty rate increased in terms of the 2$ US poverty line. Second, through testing for second order stochastic dominance using poverty deficit curves, it was proved that poverty increased no matter which poverty line was used.

However, poverty in the region is prone to fluctuation. As one can see from the transition matrix, there is reasonable movement into and out of poverty. Regarding the 1$ US poverty line 18.5 percent of the households face transitory poverty, and in terms of the 2$ US poverty line, transitory poverty increases to 34 percent of the households. Regarding the 2$ US-poverty line only 30 percent of the household can be regarded as never poor.

The analysis of the determinants of chronic and transitory poverty shows that the base characteristics of both groups are often similar, which is not very surprising. Major determinants of transient and chronic poverty are household size, non-agricultural income, and remittances received, as well as the endowment with physical, social, and financial capital.

It is, however, sometimes difficult to differentiate between the causes of poverty and its symptoms. For example, we found that (very poor) households own less transportation assets. On the one hand, they are therefore less mobile and this might foster their poverty. On the other hand, because of their poverty, they cannot afford to buy a motorcycle. In addition, the number of relatives working elsewhere and sending money tend to be lower for chronically poor households. While remittances can be a crucial part of income, chronically (very) poor people may lack the financial means to leave their villages. These kind of vicious circles can be pronounced and Barnet et al. (2008) explained that many households with low income/ expenditures are trapped in chronic poverty.

From our findings, we can draw conclusions and policy implications for poverty reduction. Poorer households have fewer opportunities to participate and derive income from non-agricultural activities, because of their lower resource endowment. Therefore, potential non-agricultural activities have to be carefully evaluated as to whether they suit the assets owned by poor households. As access to credit is likely to improve people's livelihoods as it allows investments in non-farm businesses, micro-finance schemes are an opportunity for development in the region. In addition, it is clear that social capital plays a crucial role in preventing households from poverty. Therefore, it is necessary to make organizations available for the poor, e.g. integrating the poor into these organizations or through subsidize membership fees. As low education in terms of less than primary education tends to increase the probability of becoming chronically poor and other studies find strong effects of education in general, it would be worth to invest in education schemes to strengthen people's human capital.

In general, the chronically poor need programs that enhance their physical and human capital endowments whereas the transitory poor need help to overcome certain difficult situations (Grootaert et a. 1995). Thus, insurances or income stabilization programs are particularly suited for protecting transient poor from idiosyncratic shocks. The direct transfer of income or assets could instead help the chronic poor (e.g. Baulch and Hoddinott 2000). Hulme and Shepherd (2003) point out that a pressing issue for policy is the affordable implementation of pensions for the elderly, as well as unemployment, illness and disability insurances, direct aid in emergency situations, and accessible credits schemes. Furthermore, they claim that "poverty policies based on short-term interventions, focused on creating opportunities for those who are able to escape from poverty and sustain themselves above the poverty line, are clearly not enough"(p. 417).

Baulch and Hoddinott (2000) make the point that a reduction of several sources of shocks could prevent households from falling into poverty. As a first source of shocks they name the government itself. They suggest that governments need to enhance their credibility and improve their macroeconomic policies. Further they name big covariant shocks as main causes of welfare losses. Interventions to protect the poor and vulnerable from these shocks should therefore be available *ex ante*, as often these covariant shocks (such as droughts or floods) are predictable. Such interventions for example might be area-based insurances.

Such an insurance is also a possible strategy for Central Sulawesi which is prone to periodic floods caused by heavy rainfall or by droughts caused by El Nino (see Keil 2004, Keil et al. 2008).

Regarding the methodology, more data (especially in terms of panel rounds) is likely to improve the quality of the findings. It could enlighten some categories such as the impact of female household heads or high education on the poverty status which remained somewhat unclear so far. Furthermore, more survey rounds would make the use of the components approach possible.

5. Necessity or lucre? Poverty and deforestation at the household perspective

Summary

In Indonesia, the annual deforestation rate increased from an average of 1.2 percent in the 1990s to an average of 2.0 percent between 2000 and 2005. Other than logging activities, a major source of deforestation is the expansion of agricultural areas by smallholders. By nalyzing deforestation conducted by rural smallholder farmers on the household level, we are able to overcome limitations of higher aggregated models of land-use change which often fail to take into account important household factors that like capital endowment or access to credit may determine deforestation. The purpose of this paper is to explore the underlying factors which drive rural households to clear natural forest for the cultivation of crops. It aims to identify factors which could help protect the national park by being considered in the design of policies and programs.

To account for socio-economic differences, we differentiate our analyses for three poverty groups and also integrate an index of relative poverty in our regression analysis. We use panel data from three waves of household surveys conducted between 2000 and 2006. The surveys included 266 randomly selected households from 12 villages in the vicinity of Lore Lindu National Park in Central Sulawesi, Indonesia.

The results suggest that conversion of forest into farm land in the research area is a severe problem as on average 0.2 ha were converted into farm land between 1999 and 2006 by every household. 50 percent of the area cleared is used for cocoa production. The cultivation of dry rice is with 28 percent second to cocoa cultivation. We further found that poorer households are in fact more likely to convert forest and that social capital (in terms of the participation in organizations) seems to foster the probability of forest clearance.

5.1 Introduction

Natural tropical rainforests, the richest and most valuable terrestrial ecosystem (Angelsen and Kaimowitz 1999), disappeared at an alarming rate of 0.6% per year between 2000 and 2005 (FAO 2006). Deforestation has a negative impact on climate, contributes to a loss of biodiversity, reduces timber supply, leads to flooding, salinization and soil degradation, and therefore, also affects economic activity (Angelsen and Kaimowitz 1999, Barraclough and Ghimire 2000, Walker et al. 2002). In Indonesia, the annual deforestation rate rose from 1.2% in the 1990s to 2.0% from 2000 through to 2005 (FAO 2009). Besides logging activities, which contribute significantly to deforestation in South East Asia (Angelsen and Kaimowitz 1999), a major source of deforestation is the expansion of agricultural area by smallholders (Geist and Lambin 2002, The Nature Conservancy 2005a, FAO 2005).

Several attempts have been made to evaluate different spheres of tropical deforestation (Geist and Lambin 2001). Geist and Lambin for example, analyzed “proximate causes” and “underlying driving forces” of tropical deforestation (2002). As “proximate causes” they define human activities and immediate activities at the local level. “Underlying driving forces” in their analysis are defined as fundamental social processes such as policies or population growth. Regarding the “proximate causes”, their analysis suggests that multiple factors are causing deforestation. In particular, they found that the combination of agricultural expansion, wood extraction and infrastructure expansion is evident in most studies.

In their analysis on agricultural expansion and tropical deforestation, Barraclough and Ghimire (2000) state that deforestation is a systemic problem which requires deep policy and institutional reforms at all levels and land tenure and farming systems are important in determining deforestation. Regarding the importance of farming systems, Sunderlin and Resosudarmo (1996) point out that there might be huge differences in deforestation rates between traditional shifting cultivation (which can be sustainable due to long fallows), and forest pioneering (which intends to establish permanent or semi permanent agricultural production). In the research area, forest pioneering is predominant, as the plots mostly are cleared for long-term use.

Chomitz et al. (2006) state that “(d)eforestation is undertaken by rich and poor, for gains small and large” (p. iv). Regarding the link between poverty and deforestation, the literature reveals two opposing views commonly held regarding the link between poverty and deforestation: some argue that the poor play a significant role in deforestation, while others hold that the poor have strong incentive to protect forested land. The analyses of Geist and Lambin (2001) provide evidence that poverty is a driving force for deforestation in many Asian case studies. For our research area (the Lore Lindu National Park (LLNP)), The Nature Conservancy affirms that the conversion of natural forest into farm land in is driven by severe poverty in the surrounding villages (TNC 2005a). Also Chomitz et al. (2007) found both high deforestation rates and high poverty incidence for Central Sulawesi.

Barraclough and Ghimire (2000) argue that poor settlers often rely on forest resources for fuel or fodder and they admit that these people, however, often produce food on recently cleared plots. Even though the "(…) conventional poverty-environment argument is that poor families are more likely to clear the forest, either to grow crops or to cut wood, because they have shorter time horizons (…) the counterargument says such families are less likely to do so because they lack the necessary capital to put additional land into production (…)" (Angelsen and Kaimowitz 1999, p. 76). Forests can be a substantial part of the livelihoods of rural people as they can support subsistence, generate cash income or act as safety networks (Poverty and Environment Network, PEN 2009). Forests can also fill gaps as part of the *ex ante* response to risks (e.g. to overcome seasonal fluctuations in the availability and affordability of goods), and they can act as a form of insurance for larger shocks such as droughts *ex post* (Wunder 2001). Therefore poor rural households would have multiple reasons to protect forested areas. Although a large share of the population in the research area depends on forest products (Schwarze et al. 2006), deforestation in the area is ongoing.

In our research, the link between poverty and deforestation is explored. Existing studies on this issue (e.g. by Chomitz et. al. 2006, Godoy et al. 1997; 1998; 1998a) mainly focus on deforestation by (indigenous) forest dwellers, and not on deforestation by people living at the forest margins. Research currently conducted by the Center for International Forestry (CIFOR) focuses on the potential of forests for income generation and thus assessing the role of forests in poverty alleviation (CIFOR 2010). As there is not much literature focusing on the connection between poverty at the forest margin and forest clearance, our work contributes substantially to research on linkages between poverty and deforestation.

Little is known about how the characteristics of the “agents of deforestation” (those who are responsible for clearing) affect their behavior (Angelsen and Kaimowitz 1999). By using household level data we are able to overcome limitations of higher aggregated models of land-use change which often fail to take into account important household factors like capital endowment or access to credit. The aim of this paper is to reveal the underlying factors which drive rural households to clear natural forest for the cultivation of crops. Using the area in the vicinity of the LLNP in Central Sulawesi, Indonesia as an example, this paper focuses on the decision-making processes of households concerning the conversion of forest into agricultural land. It helps to identify factors which can help design policies and programs aimed at protecting the national park. Specifically, the following research questions will be addressed: (1) How much natural forest was cleared by rural households? (2) What crops are grown on these plots? (3) Are there any differences between poor and wealthier households? (4) What are the influential factors determining decisions to clear natural forest? (5) What determines the extent of forest area cleared? The outline of the paper is as follows: In section 5.2, a summary of the sampling method and data collection is presented. In section 5.3, we discuss the conceptual framework used as well as methodological issues. In section 5.4, both the results of our descriptive analysis and our econometric analysis are displayed. In the final section, we draw final conclusions and derive policy implications from our analysis.

5.2 Sampling method and data collection

The sampling procedure was a stratified random sample. The data were collected in 12 villages in the vicinity of LLNP in Central Sulawesi, Indonesia. For a description of the sampling frame and sampling procedure see Zeller et al. (2002). Household and plot level data was collected through standardized, formal questionnaires from 266 households. The same households have been interviewed in the years 2000/2001, 2004 and 2006.

5.3 Conceptual framework and methodological issues

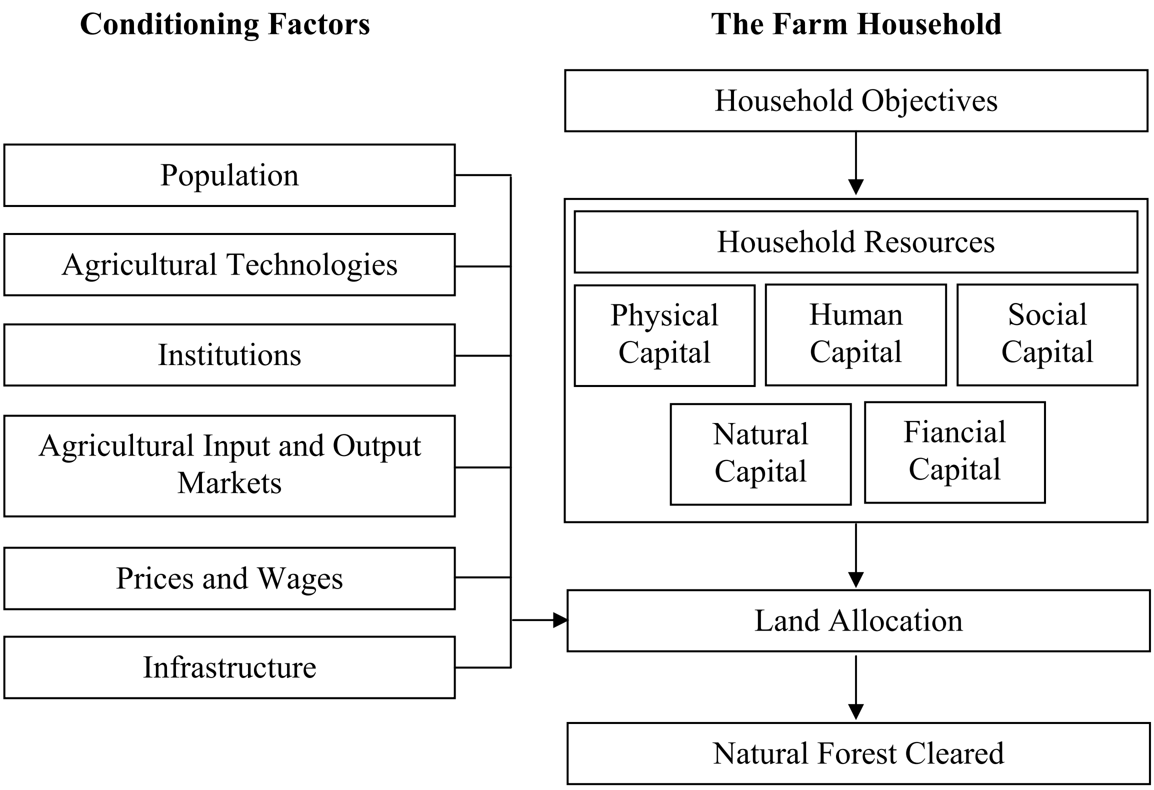
5.3.1 Conceptual framework

Angelsen and Kaimowitz (1999) propose five components for the analyses of deforestation (see also Kaimowitz and Angelsen 1998, Sunderlin and Resosudarmo 1996):

- The magnitude and location of deforestation
- The agents of deforestation
- The choice of variables (the decision about land allocation that determines the level of deforestation by the agent)
- The agents decision making parameters (parameters which directly influence the decision of the agents, but are external to them)
- Macroeconomic economic variables

They argue for grouping these components on three major levels and they suggest starting with the identification of the agents of deforestation and their relative importance for deforestation (in terms of their contribution). The actions of the identified agents Angelsen and Kaimowitz (1999) name “sources of deforestation”. The decision parameters, which are based on the characteristics of the agents such as background, preferences and resources, but as well as on prices, technologies, institutions, information, access to services, infrastructure etc. are seen as immediate causes of deforestation. Broader forces that determine the agent’s characteristics and decision parameters are described as underlying causes. Examples for underlying causes are the market, infrastructure development, institutions (especially the property regime), etc.

As our analysis refers to the household level, we mainly analyze the “sources” and the “immediate causes” of deforestation. Building on the framework of Angelsen and Kaimowitz (1999), we further define the internal and external parameters which are influencing the land allocation decision made by households. Doing so, we differentiate a set of conditional factors which influence the land allocation of farm-households and therefore, the decision to clear natural forest. Regarding the internal factors, the land allocation decision is influenced by the household resource endowment with physical, human and social capital, as well as by the overall household objectives (Figure 11).



Source: own construction

Figure 11: Conceptual framework of land allocation decision by rural households

To capture the effects discussed above, we have included the variables described in Table 24 as independent variables in our models. In the research area, many farmers cultivate wet rice on irrigated rice fields. We incorporated the percentage "share of irrigated rice fields owned" into the analysis, as a proxy for technology adoption, which can play an important role in reducing the pressure on forests (Nuryartono 2005, Maertens 2006). The age of household head is considered an important demographic variable (proxy experience). The number of adult household members ranges from 1 to 8, and can be used as a proxy for the availability of labor force within a household, which is important in this analysis. For example, land clearing in rural Peru is highly depended on the available labor force (Zwane 2005).

To represent education, we used an ordinal variable ranging from 1 (never attended school) to 8 (attended academy or university). We assumed that higher education might decrease the probability of deforestation by rural households, because especially higher education might address environmental problems. Furthermore, we wanted to test for the influence of social capital on the households land allocation decision. Social capital is represented by the mean number of organizations to which all adult household members belong. We hypothesize that presence of social capital increases trust and empowerment and therefore enhances a sustainable treatment of forest resources (cf. Meyer et al 2003, Rodruíguez and Pascual 2004).

In addition, migrant households may foster deforestation by buying plots cleared by local people in order to grow cocoa on the former forest plots (Weber et al. 2007). Therefore, we included a dummy variable indicating whether the household head is migrant or indigenous. Non-agriculture income is widely assumed to reduce deforestation. To proxy a household's market access we used a variable indicating how far the household lives from the closest road in walking hours. We also included a dummy variable for "credit availability" in our analysis (measured as whether the household received a formal credit within five years prior to the survey in 2000) because it is likely that available credit finance deforestation (Angelsen and Kaimowitz 1999), as they for example increase the household's ability to invest in an extension of perennial crop production which was found to be a major cause of deforestation in the research area (Schwarze et al. 2006). However, Godoy et al. (1996; 1997) found that credits reduced deforestation conducted by forest dwellers in Bolivia and Honduras.

In addition to the factors mentioned above, property rights may have effects on deforestation, but the role is not clear (Geist and Lambin 2002). However, there is some evidence that tenure insecurity increases deforestation (Godoy et al. 1998). Therefore, we controlled for land tenure (represented as share of titled land owned) in the vicinity of LLNP. As the agricultural land use in the research area is very location specific depending on local rainfall, topography and soil conditions (Keil et al. 2008), we also controlled for agro-ecological and other regional differences by including sub district dummy variables. All variables included in the analyses were lagged variables. Thus always the values from 2000 were taken to explain deforestation in the subsequent years.

Table 24: Variable description and summary statistics (independent variables)

Variable	Mean	Std. Dev.	Min	Max
Poverty index	-0.014	0.97	-1.84	2.87
Percent of irrigated rice fields owned	27.16	35.13	0	100
Age of household head	43.97	14.33	20	83
Number of adult household members	3.46	1.63	1	8
Maximum level of schooling	4.91	1.77	1	8
Mean number of memberships in organizations per adult	0.93	0.74	0	3.5
Ethnicity of household head (1=non-indigenous)	0.19		0	1
Household gained non-agricultural income(1=yes)	0.15		0	1
Walking distance house - road (in hours)	0.92	2.7	0	13
Household has credit available (1=yes)	0.15		0	1
Share of land with title owned (%)	26.3	42.5	0	100
Sub district id Lore Utara (1=yes)	0.28		0	1
Sub District is Sigibiromaru (1=yes)	0.31		0	1
Sub District is Kulawi (1=yes)	0.27		0	1

Source: own calculation with STORMA data from 2000; N=266

5.3.2 Descriptive analysis

The first two research questions of how much natural forest was cleared by rural households, and of what crops are grown on these plots can be answered by looking into descriptive statistics over the three survey rounds. The third question of whether there are any differences between poor and wealthier households, we can approach by applying a poverty index calculated by Abu Shaban in 2001 (see Zeller et al. 2003) for the research area. In his work, he used the method proposed by Zeller et al. (2001; 2003; 2006 and Henry et al. 2003) to develop an operational tool for the assessment of relative poverty levels using principle component analysis (PCA). For generating the poverty index, information on different dimensions is collected (Zeller et al. 2006). The included dimensions have been found to be robust across heterogeneous cultural and geographical settings. However, the combination of indicators and weights that is the most appropriate is area-specific and represents the local conditions (Henry et al 2003). The range of poverty dimensions seeks to include credible information on indicators which can be obtained quickly and inexpensively (Zeller et al. 2006). The index is computed for each household in the sample. First, all data is aggregated at the household level and then, it is determined which variables are the strongest measures of relative poverty by ranking all variables according to their correlation to a benchmark variable in terms of significance. In the case of Central Sulawesi, the benchmark variable was "daily per capita expenditures for footwear and clothing". Finally, those variables stay in the model, which are highly significant in determining the benchmark variable. Therefore, the variables in the model should account for significant differences in the relative poverty levels, and reflect different aspects of poverty (Abu Shaban 2001). Using PCA, the information is aggregated into a composite index. With PCA, a mix of indicators is determined that can be most effectively combined to measure the relative poverty status of a household. The idea of principle component technique is to slice information in the *set* of indicators into several components. Each component is constructed as a unique index based on values of all indicators (cf. Zeller et al 2006). The components integrated in the poverty index for the research area can be found in appendix XI. According to the work of Abu Shaban (2001), we differentiated three poverty groups: the poorest (poverty group 1), the poor (poverty group 2), and the less-poor (poverty group 3) in the base year 2000. The poverty index ranges from –1.84 for the poorest household to 2.87 for the richest household.

In our analysis, we want to discover whether the relative poverty status in 2000 had any influence on forest clearance in the subsequent years and how the crops cultivated differ between the socio-economic groups in the subsequent years.

5.3.3 Econometric analysis

We conducted our analysis of determinants of forest clearance at the household level. Another possibility would have been to analyze the determinants at the plot level. Bekele and Mekonnen (2010) point out that decisions of an action (as to clear land) and its intensity may not be made uniformly for the entire farm (all plots) of a household. Additionally, Saint-Macary et al. (2010) argue that a household-level model is unable to capture the effects of soil characteristics, and other plot-specific variables on adoption (clearance in our case). However, the same authors found a much better prediction power by their household-level analysis than by their plot-level analysis regarding the adoption of soil conservation techniques in northern Vietnam.

Our analysis refer to newly acquired plots. Therefore, we assume that the decisions to clear and where to clear are uniformly made for by the households for each new plot. Furthermore, we are primarily interested in the factors which influence the general decision to clear and therefore refer to a household level analysis. The decision to clear natural forest is measured by a binary variable, which is zero if the household did not clear any natural forest since 1999. It takes on the value one if the household cleared forest since this time. We are interested in how the vector of explanatory variables influences the possibility that the binary dependent variable takes on the value 1. The binary response probit model is estimated by Maximum Likelihood Estimation (MLE) using the computer package Stata 10.

A probit model is defined as

(17) $$P = (y_i \neq 0 \mid x_j) = \Phi(x_j b),$$

where P is the probability, y_i is the dependent variable (in our case forest clearance between 1999 and 2006), x_j is the independent variable (in our case household characteristics), Φ is the standard cumulative normal distribution, and $x_j b$ is the probit score. The coefficients of the probit model are difficult to interpret, because an increase in x_1 by one unit increases the probit score by b standard deviations. Therefore, we display the marginal effects which are based on the change in probability calculated at the mean.

The marginal effect is given as

(18) $$\frac{\partial \Phi}{\partial x_1} = \text{ø}(\bar{x}b)b_1,$$

where $\frac{\partial \Phi}{\partial x_1}$ is the probability of a change in x_1. Thus the marginal effect is the probability for an infinitesimal change in each independent continuous variable. For dummy variables the discrete change is reported (STATA 2007).

After modeling the household determinants of deforestation, we employed analysis of how much forest is cleared. The dependent variable "size of plots cleared since 1999" is censored at zero, therefore we used a tobit model. A tobit model is a common model to estimate the relationship for limited dependent variables (Tobin 1958, Godoy, et al. 1998).

One major criticism on the tobit model is that it has the restrictive assumption that all zeros arise from factors as economic and demographic characteristics alone and that the model therefore ignores zero-observations due to respondents non-participation decisions (Wodjao 2007).Wodjao argues that in his study on computer and internet use in the US the observed zeros might have two sources. On the one hand he finds behavioral zeros if people do not own a computer (2007). This case is similar to the case of households that do not clear forest in our study. On the other hand he observes random zeros if people own a computer but do not use it the diary (i.e. survey) day. He tests two kind of models which account for the latter problem. On the one side the Heckman model (Heckman 1979) which addresses the problem of zeros due to non-participation decisions. Its argument is that an estimation on a selected sub-sample (a censored estimation) results in a sample selection bias. The also called heckit model therefore estimates a two step estimation procedure, (1) a full sample probit, followed by (2) a censored estimation. Firstly the probability of a positive outcome is estimated and secondly a conditional equation on the level of participation. In heckit it is possible to use different sets of variables in each step. In the Heckman model it is assumed that zeros mainly arise from respondents self-selection and therefore from his or her deliberate choices (Wodjao 2007). Another possibility to overcome the restrictive nature of tobit is the so called double hurdle model (Cragg 1971). This model assumes two hurdles have to be overcome to observe positive outcomes. It accounts both for the ownership or participation decision and for the random circumstances of its intensity of use. Like in the Heckman model different variables can be used in each of the two equations.

In our case the problem of two separate decisions is less likely, as land is scarce in the region and therefore the decision to clear is closely related to the decision on how much land is cleared. Hence it seemed not necessary to take different sets of explanatory variables . Thus we referred to the traditional tobit approach. Following Cong (2000), the tobit model can be written as

(19) $$y_i^* = \begin{cases} y_i, \text{ if } a < y_i < b \\ a, \text{ if } y_i \leq a \\ b, \text{ if } y_i \geq b \end{cases}$$

where y_i is a latent variable, a is the upper limit, b is the lower limit. Instead of observing y, we observe y_i*, which is bounded between a and b if y_i is outside of those bounds (STATA 2007a). In our case the decision of how much land is cleared is obviously bound to the decision regarding if land is cleared. Not all of the households within the sample cleared forest, thus information on the size of the cleared plots is only available for 41 households (referred to as uncensored observations).

For the tobit model we also displayed marginal effects additional to the coefficients, as the *ß* coefficients (which express the change in the mean of the latent dependent variable) (Cong 2000), are difficult to interpret.

For tobit models, several marginal effects can be of interest. Therefore, we describe shortly the one we used. In the results section the marginal effects for the expected value of the dependent variable (conditional on being uncensored) are displayed,

(20) $$\partial E(y^* \mid \text{a} < \text{y*} < \text{b}) / \partial x_1 ,$$

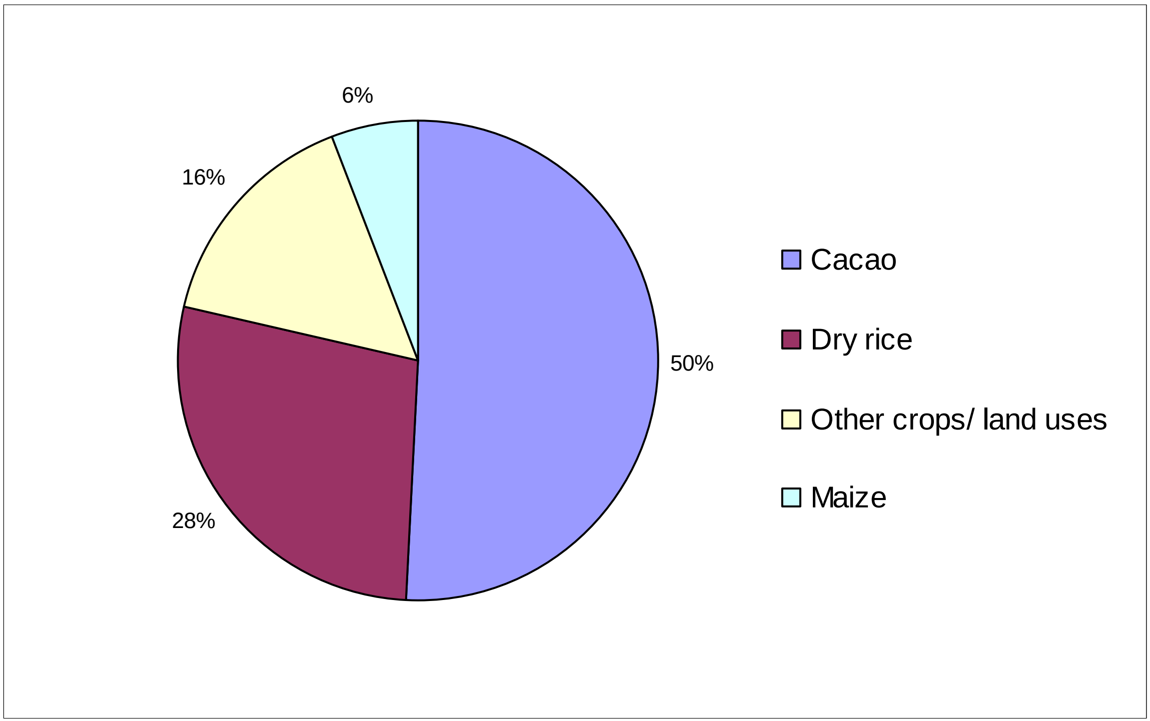
where $\partial E/\partial x_1$ represents changes in the conditional expected value of the dependent variable (Cong 2000), a is the lower limit for left censoring and b is the upper limit for right censoring (STATA 2001).

5.4 Results

5.4.1 Results from descriptive analysis

Over the six year period, the smallholder farmers in the sample (N = 266) cleared 53 hectare (ha) of primary rainforest. As there are living around 132,000 people in about 26,000 households in the research area (ANZDEC 1997, Maertens et al. 2002), and our sample is representative (Zeller et al. 2002) we can extrapolated our finding to the entire population in the research area. Doing we can state that approximately 52 km^2 of natural forest were cleared by smallholder farmers. Thus we observe an average annual deforestation rate of 0.2 percent. In an analyses of deforestation in the research area between 1972 and 2002 based on satellite images, Erasmi et al. (2004) found a slightly higher rate of 0.6 percent per year. Both findings are still lower than the average annual deforestation rate of 1.7% between 1985 and 1997 for Sulawesi (FWI/ GIF 2002).

The 53 ha were cleared by 41 households (15.4% of the sample). Of course some of the households cleared more than one plot of forest area in the respective time span. Over the period of investigation, 62 forest plots of plot sizes (between 0.01 and 5 ha each) were cleared. On the plots, different crops where cultivated and the shares of crops grown can be found in Figure 12.



Sorce: own calculation with STORMA household survey data from 2000/2001, 2004, and 2006; N= 266

Figure 12: Area cleared for major crops in % (1999-2006)

In Table 25, the crops as well as the amount and size of the plots are displayed for every year.

Table 25: Crops cultivated on former forest plots, # of plots cleared (total ha)

Crop grown	2000	2001	2002	2003	2004	2005	2006	Total
Cacao	5 (2.2)	3 (5.5)	1 (5)	4 (4.5)	1 (1)	2 (3.5)	-	16 (21.7)
Dry rice	11 (8.7)	-	1 (1)	2 (1)	1 (1)	-	6 (4.5)	21 (16.2)
Maize	2 (1)	-	-	-	3 (3.2)	2 (1.3)	1 (0.3)	8 (5.7)
Other crops/ land uses	3 (2)	2 (2.4)	-	3 (1.1)	4 (2.3)	4 (3.1)	1 (0.7)	17 (11.5)
Total land deforeste d	21 (13.9)	5 (7.9)	2 (6)	9 (6.6)	9 (7.5)	8 (7.9)	8 (5.5)	62 (55)

Source: own calculation with STORMA household survey data from 2000/2001, 2004, 2006; N= 266

Note: values are not weighted

Figure 12 as well Table 25 show, that the major share of cleared total area was dedicated to cacao production (50%). Cacao was cropped in six out of seven years. The next important land use, was cropping of dry rice (28%). New plots for dry rice cultivation were cleared in five out of seven years. These figures suport the finding of Weber et al. (2007) that a shift in livelihood strategies from “food crops first” to “cash crops first” by rural farmers in the research area occurs. However, Geist and Lambin (2002) state that the expansion of food-crop cultivation for subsistence was found to be three times more frequently reported than the expansion of commercial farming.

Forest clearance did not occur in all surveyed villages and the deforestation shares among villages differ largely. This, of course, has partly to do with the distance of the villages to the forest and the National Park.

In Table 26, differences between poor and wealthier households are displayed. As mentioned before, 15.4% of the sample households cleared forests. Among the poorest households 31.8% cleared forests, while this was the case only for 3% of the better-off households. The mean area cleared was 1.3 ha on average for all households. Here the "poor", i.e. the medium tercile, cleared the biggest share on average (2.1 ha). Food crops as upland rice and maize are mainly cultivated by the poorest and the poor. The mean share of cocoa instead is very high for the less poor: 66.67 percent of the plots cleared by this group is cultivated with cocoa, the major cash crop grown in the area.

Table 26: Area cleared and crops grown between 1999 and 2006 by poverty status

	All house-holds	Poverty group 1 (poorest)	Poverty group 2 (poor)	Povert y group 3 (less poor)
Household cleared natural forest since 1999 (%)	15.4	31.8[abc]	11.4[abc]	3.3[abc]
Mean area cleared since 1999 conditional on clearing (ha)	1.3	1.1[abc]	2.1[abc]	1.1[abc]
Mean area share maize conditional on land cleared since 1999 (%)	11	12.6	10	0
Mean area share upland rice conditional on land cleared since 1999 (%)	34.3	41.9	23.3	0
Mean area share cocoa conditional on land cleared since 1999 (%)	22.5	19.9	16.7	66.7
Mean are share other land uses conditional on land cleared since 1999 (%)	32.1	25.6	50	33.3

Source: own calculation with STORMA data from 2000-2006; N= 266

Note: Homogeneous subsets (a, b, c) based on Mann-Whitney Test, P < 0.05

5.4.2 Results from econometric analysis

We used two different regression models to evaluate the determinants of deforestation and its extent.

To evaluate the determinants of deforestations, we employed a binomial probit model, where the dependent variable was 0 if no forest was cleared between 1999 and 2000, and 1 if forest was cleared. We employed several indicators as proxies for conditional factors such as agriculture technologies (in terms of irrigated rice fields), institutions (in terms of tenure security), and infrastructure (in terms of distance between house and road) as well as the household's endowment with human, social, and physical capital according to our conceptual framework. Using the *collin* ado in STATA statistical software package, we found no evidence of multicollinearity between the variables. The results of the probit model are displayed Table 28. The coefficients (marginal effects) in the table can be interpreted as the percentage change in the probability for an infinitesimal change in each independent, continuous variable and the discrete change in the probability of a dummy variable.

Table 28: Probit results for the decision to clear natural forest

Dependent variable: Household cleared forest between 1999 and 2006 (1=yes) / **Independent variables**	**Marginal effects (dF/dx)**	**Robust standard error**	**z-value**
Poverty index	-0.0450121	0.0183373	-2.82***
Percent of irrigated rice fields owned	-0.0003461	0.0004278	-0.79
Age of household head	-0.0021366	0.0010243	-2.15**
Number of adult household members	0.0096498	0.0083475	1.19
Maximum level of schooling	0.0035817	0.008378	0.43
Mean number of memberships in organizations per adult	0.0444487	0.0190431	2.44**
Ethnicity of household head (1=non-indigenous)[a]	0.0321715	0.051661	0.73
Household gained non-agricultural income(1=yes)[a]	0.0285245	0.0438568	0.72
Walking distance house - road (in hours)	0.000015	0.0034195	0.00
Household has credit available (1=yes)[a]	-0.0409318	0.0220805	-1.25
Share of titled land owned by household (%)	-.0006127	0.0003439	-1.98**

Source: own calculation with STORMA data from 2000-2006; N= 266

Note: ***significant at the 1% level, ** significant at the 5% level, *significant at the 10% level, [a] dF/dx is for discrete change of dummy variable from 0 to 1, z corresponds to the test of the underlying coefficient being 0, [b]in contrast to Sub district Palolo

Table 28 continued: Probit results for the decision to clear natural forest

Dependent variable: Household cleared forest between 1999 and 2006 (1=yes) / Independent variables	Marginal effects (dF/dx)	Robust standard error	z-value
Sub district id Lore Utara(1=yes)[ab]	0.0141741	0.0416765	0.37
Sub District is Sigibiromaru (1=yes)[ab]	-0.0700762	0.0344618	-1.75[*]
Sub District is Kulawi (1=yes)[ab]	0.0899813	0.0652783	1.85[*]
Pseudo R^2		0.3272	
Wald Chi^2		58.73	
Probability > Wald Chi^2		0.0000	
% correctly predicted		84.2%	

Source: own calculation with STORMA data from 2000-2006; N= 266

Note: [***]significant at the 1% level, [**] significant at the 5% level, [*]significant at the 10% level, [a] dF/dx is for discrete change of dummy variable from 0 to 1, z corresponds to the test of the underlying coefficient being 0, [b]in contrast to Sub district Palolo

From these results, we see that poverty increases the probability of deforestation significantly. Our results suggest that an increase in the poverty index by 1 standard deviation (an increase in wealth), reduces the likelihood of encroachment by 4.5 percent. Interestingly, we did not find any significant influence of the share of irrigated rice fields owned in the base year 2000 on the probability of forest clearance. However, households headed by younger household heads are significantly more likely to clear forest than households headed by older household heads. This finding is consistent with findings by Nuryartono (2005). In addition, the maximum level of education for household members had no impact on the decision to clear forest. This is in contrast to findings in Bolivia where each additional year of education lowered the probability of rain forest clearance by indigenous households by 4 percent (Godoy et al. 1998a). Interestingly, households with higher memberships in organizations had a significantly higher probability to clear forest than households with a low membership levels.

In Indonesia, non-farm employment can have a significant effect on reducing the pressure on rainforests (Purnamasari 2008). For Honduras, Godoy et al (1997) found a similar relationship. Unfortunately, our analysis does not further support this important issue.

The walking distance from the household's dwelling to the road and the access to credit did not have an impact on the likelihood to clear forest. As expected, the share of titled land has a significantly negative effect on deforestation. It makes sense that households with secure tenure rights are less likely to encroach forest areas than households lacking land titles and this has been documented in Bolivia (Godoy et al. 1998) and Honduras (Godoy et al. 1997). The probability of deforestation is significantly higher for households in the sub-district of Kulawi and significantly lower for households in the sub-district of Sigibiromaru. This can be explained by the distance to the forest: While Sigibiromaru is relatively close to the regional capital of Palu, the Kulawi sub-district is located right at the forest border.

In the second regression analysis, we employed a tobit regression model to take the size of the cleared area into account. The results are displayed in Table 29.

Table 29: Tobit results for the decision on how much natural forest is cleared

Dependent variable: Size of cleared forest plots aggregated from 1999 to 2006 (in are) Independent variables	Coefficients	Marginal effect $\partial E / \partial x_1 =$ E (size of plots | size of plots >0)	z-value of marginal effect
Poverty index	-113.5565	-15.75315	-2.18**
Percent of irrigated rice fields owned	-1.067473	-0.1480854	-1.02
Age of household head	-5.157721	-0.7155059	-2.20**
Number of adult household members	13.4856	1.870792	0.74
Maximum level of schooling	17.05569	2.366054	0.78

Source: own calculation with STORMA data from 2000-2006; N= 266

Note: 225 left-censored observations at plot size<=0, 41 uncensored observations, 0 right-censored observations, ***significant at the 1% level, **significant at the 5% level, *significant at the 10% level, [a]dF/dx is for discrete change of dummy variable from 0 to 1, [b]in contrast to Sub district Palolo

Table 29 continued: Tobit results for the decision on how much natural forest is cleared

Dependent variable: Size of cleared forest plots aggregated from 1999 to 2006 (in are) / Independent variables	Coefficients	Marginal effect $\partial E / \partial x_1 =$ E (size of plots | size of plots >0)	z-value of marginal effect
Mean number of memberships in organizations per adult	99.15963	13.75594	2.02**
Ethnicity of household head (1=non-indigenous)a	128.384	19.58513	1.16
Household gained non-agricultural income (1=yes)a	21.59474	3.047205	0.30
Walking distance house - road (in hours)	-1.216847	-0.1688074	-0.19
Household has credit available (1=yes)[a]	-134.841	-16.81958	-1.33
Share of land with title owned (%)	-1.36375	-0.1891865	-1.72*
Sub district id Lore Utara (1=yes)[ab]	7.333254	1.022706	0.09
Sub District is Sigibiromaru (1=yes) [ab]	-171.6469	-22.68365	-1.82*
Sub District is Kulawi (1=yes) [ab]	129.128	19.4692	1.52
/sigma		242.7324	
F (14, 252)		3.20	
Prob > F		0.0001	
Pseudo R^2		0.0980	

Source: own calculation with STORMA data from 2000-2006; N= 266

Note: 225 left-censored observations at plot size<=0, 41 uncensored observations, 0 right-censored observations, ***significant at the 1% level, **significant at the 5% level, *significant at the 10% level, [a]dF/dx is for discrete change of dummy variable from 0 to 1, [b]in contrast to Sub district Palolo

The results of the tobit model are similar to those of the probit model, even if at slightly lower significance levels. The tobit model accounts for both, the probability to clear forest and the decision regarding how much land to clear. The marginal effects displayed in Table 28, refer to the changes in the conditional expected value of the dependent variable. Again poor households are more likely to convert larger areas than wealthier households. The same is the case for households headed by younger household heads. Households with higher social capital also clear larger areas. Like in the probit model, the decision on how much land is cleared is significantly negatively influenced by land tenure, with greater land tenure security on the already owned land leading to less deforestation. The only variable which was not significant was the district dummy for Kulawi, the sub district directly located at the forest border. Thus the decision on how much land is cleared did not depend so much on the household's location.

5.6 Conclusions and policy implications

Given these results, one can evaluate the ways in which deforestation may be reduced. Forest resources are used widely by households living in the vicinity of the Lore Lindu National Park, and in the research area 76% of the households collect forest products (Schwarze et al. 2007). Specifically poor households rely on forest products like rattan as an additional income source. For the poorest tercile of the households, income from selling forest products has been found to account for 21% of total household income (Schwarze et al. 2006). This situation is similar to the one from East Kalimantan described by Purnamasari (2008) where 85% of the households have some kind of forest income and again poor farmers are more dependent on forest income than better-off farmers.

However, in contrast to the analysis of Purnamasari (2008), who found poor Indonesian smallholders are less likely to clear natural rainforests, our analysis suggests that poverty fosters deforestation, at least in the vicinity of LLNP. Therefore, we have reason to assume that degradation will continue if poverty in the area persists. Thus we can conclude that poverty reduction in the region is crucial not only to improve peoples' livelihoods, but also to protect the natural rainforest. However, Zwane (2005) found for rural areas in Peru that poverty reduction would not hold to reduce deforestation. He state that small increases in income will not reduce the rate at which smallholder households clear land. Also Chomitz et al. (2006) doubt that added income will people deter from deforestation.

In our research area, natural rainforest is mainly cleared to grow cacao, followed by the cultivation of dry rice which is a subsistence crop. As relatively poorer households are more engaged in the cultivation of dry rice and maize one can argue that they need more space to grow subsistence crops for food production. Nevertheless, the biggest area share is dedicated tot cocoa production which could indicate that cash crop production is seen as a pathway out of poverty, even if there is no empirical evidence so far. However, newly cleared plots are often cultivated with annual crops like maize and beans to make the forest plots arable before the transition to cocoa.

As mentioned above, forest is often cleared by local households but later sold to migrant households (Weber et al. 2007). In the latter case the question should be asked who then is the “agent” of deforestation: the poor household who cleared the plot, or rather the rich household who bought the plot afterwards (most likely to grow cocoa). A similar kind of discussion on the correct terminology was raised by Sunderlin and Resosudarmo (1996). The discrepancy between these views, i.e. who is the intrinsic deforestation agent, can also be supported studies by Schwarze et al. (2006; 2007). The authors found that perennial crops as coffee or cocoa in the research area are mainly grown by wealthier households and that the cultivation of these crops is a major source of deforestation. Regardless, the pressure on forests induced by the extension of tree cropping could be reduced by enhancing the technical efficiency of existing tree crop production as concluded by Keil et al. (2007). However, increased revenues by efficient cocoa cropping could make cocoa cropping more attractive and therefore increase deforestation.

Membership in organizations, which we used as proxy for social capital, normally is seen as very positive for the poor, as ties to extended family members and one’s community can help absorb shocks as the onset of disability etc. (Gertler et al. 2006) and therefore strengthen a household resilience (Keil et al. 2008). However, our analysis suggests that these memberships foster deforestation. Possible reasons are that “spillover-effects” are channeled through these organizations and that organization-members have access to additional labor force (other members). Therefore, qualitative research on the role of different organizations in the process of deforestation is needed. Capacity building regarding the negative consequences of deforestation within local organizations could help building awareness.

Another component determining deforestation is land tenure. As a lack of secure land titles enhances the probability that a household will clear forest, it is urgent to find ways to guarantee land property rights. Unfortunately, the process of getting a land title is very complex and costly (Nuryartono 2005, Klasen et al. 2010). Thus only 20% of the land has a land title at all. Migrants often purchase land, often former forest plots, from local people. Sometimes these plots are sold without legal transfer or land certificate. But also land which is inherited often does not have any formal land title. Another complication is that there are different types of land titles ranging from pretty insecure and time-restricted ones issued by the *kepala desa* (the village head) to very secure, but expansive titles issued by the BPN (Badan Pertahanan Nasioinal, the national agriculture board). Even if there was a program (PRONA) to subsidize the certification of land titles the problem is still prevalent (Nuryartono 2005, Klasen et al. 2010).

To summarize, important implications for the protection of LLNP have to include the reduction of poverty, awareness building within local institutions regarding the negative consequences of deforestation, and the enforcement of land titling of other than the encroached plots.

Interestingly, the Indonesian commitments to the Consultative Group on Indonesia (CGI) which concern forest and forest policy, does not take issues as poverty or land tenure security for the sake of forests into account. Instead it deals with illegal logging, timber production, forest fires, and over all forest management issues (FWI/ GIF 2002). However, for the design of projects dealing with both the reduction of deforestation and poverty alleviation in the research area, these commitments do not seem suitable. For achieving the goals of poverty reduction and to slow down deforestation, the above mentioned strategies seem more suitable. The already existing „Community Agreements on Conservation" (Birner et al 2006) in the region, the World Bank's Forest Strategy and Operational Policy (World Bank 2004), the REDD (Reducing Emissions from Deforestations and Degradation) mechanism (REED-I 2009), and Payments for Environmental Services (PES) schemes (e.g. Seeberg-Elverfeldt 2008, Seeberg-Elverfeldt et al. 2009) are possible frameworks for such a project.

In the future, it would be interesting to include some additional physio-geographic parameters as slope or soil quality into the analysis. Deininger and Minten (2002) found such factors being the major determinants of forest conversion in two Mexican provinces. Additionally, an extended period of observation, i.e. more survey waves, would be an advantage.

6. Overall conclusions

This study highlights three aspects of rural poverty in Indonesia. It addresses the challenges of poverty measurement, explores poverty dynamics in Central Sulawesi, Indonesia, and analyses the link between poverty and deforestation in the area. In this section, I summarize the findings with respect to the research questions raised in the introduction and I draw overall conclusions regarding the treated themes as well as the methodology used.

The findings show an overall increase in poverty over the time span of the research and reveals a crucial link between poverty and deforestation in the research area. The incidence of severe poverty (less than 1 US$ PPP per capita and day) of 18.2 percent, as well as poverty incidence (less than 2 US$ PPP per capita and day) of almost 60 percent in 2007 reveal high levels of poverty. The study also shows overall increase in deforested area over time. Extrapolating from the sample households to the entire population in the research area, rural households cleared approximately 53 km^2 of forest land between 1999 and 2006. This increasing deforestation was found to be linked to wealth status of households residing in the vicinity of forest areas.

Based on the 1 US$ poverty line, the poverty headcount ratio for Indonesia is 7.5%, averaged over the period 1990 to 2005 (HDR 2007/2008). For the same period, the national poverty headcount ratio based on the 2 US$ poverty line is 52.4% (HDR 2007/2008). This is similar to the 2 US$ poverty headcount ratio observed for the research area by my study for the year 2005. Unfortunately, more recent estimates for entire Indonesia are not available. Accompanying these high poverty incidences at the national level, however, is a decline in the country's forest cover. Between the years 2000 and 2005, the overall loss of primary forests in Indonesia was 72,390 km^2. By the year 2005, Indonesia had about 487,000 km^2 of primary forest left, accounting for 55% of the total forested area in Indonesia (FAO 2006). Relative to the national forest cover, the Lore Lindu National Park that covers most of the forest land in our research area initially covered 2170 km^2 of primary forest when it was established in 1977 (TNC 2005).

6.1 Thematic conclusions

In Chapter 2 and 3, four research questions were answered.

1. Is a regionally calibrated poverty assessment tool robust over time?

The analysis shows that the set of poverty indicators revealed in 2005 were still capable of detecting very poor households in 2007 based on absolute poverty measurement. However the models tend to over-predict the very poor. Based on the accuracy performance of both models and the comparison across the survey years, we recommend Model 2 (a set of easily verifiable indicators) and the corresponding coefficients derived from the one-step quantile procedure in 2005 as accurate tool for poverty assessment in the research area. In 2005 the poverty accuracy of this tool was 74.07 %, the undercoverage was 25.93 %, the leakage was 27.78 %, and the PIE was 0.36%. Using the same tool for poverty prediction in 2007, the poverty accuracy was 73.53 %, the undercoverage was 26.42 %, the leakage was 88.86%, and the PIE was 11.7%.

2. Is a nationally calibrated poverty assessment tool robust over space?

Compared to our regionally calibrated poverty assessment tool, the nationally calibrated tool provided by the IRIS Center and USAID for Indonesia was found to be unsuitable for predicting absolute poverty in Central Sulwaesi. When applying the tool (in terms of indicators coefficients) to our dataset (which includes all information needed), the accuracy performance was highly inaccurate. USAID calibrates its tool using the median national poverty line. Applying this poverty line, the poverty accuracy was 0 %, the undercoverage was 100% and the leakage was 211.11%. Also the PIE was with 39% quite high. Additionally, we tested the USAID indicators against the international poverty lien of 1$ US. Doing so, again the poverty accuracy was 0%, but the PIE was only 0.71%.

3. How does the indicator composition of the regional tools change when models are re-estimated?

When re-estimating the models with the 2007 data-set, the accuracy levels of both new models were similar to the ones of 2005. However, the indicator composition in Model 1 (which allows all indicators to enter the model) changes almost completely while the “dimensions” of the indicators remain similar. On the other hand, about a third of the indicators in Model 2 remain the same, presumably due to the long-term characteristics of the “easy-to-verify” indicators included.

4. Does an easily applicable poverty assessment tool like Model 2 overlook the transient poor?

The accuracy results for the transient poor are indeed worse than for the chronic or non poor. However, this is also true for Model 1.

The findings from Chapters 2 and 3 show that indictor-based assessment of absolute poverty involving a small set of indicators is possible. However, regionally calibrated tools are by far preferable to nationally calibrated tools, at least in a diverse country like Indonesia. A shortcoming of the regionally calibrated tool was the over-prediction of very poor households after two years. This calls for regular re-calibration of the tool. However, the inter-calibration period might be longer than two years since our analysis shows that similar indicators enter the models when the tools are re-calibrated.

Chapter 4 answers three questions relating to dynamics of poverty.

5. How did the poverty situation in the vicinity of the Lore Lindu National Park change between 2005 and 2007?

At a first glance, severe poverty (less than 1$ US per capita and day) appear to have decreased. However, deeper analysis shows that people in the research area got poorer in overall. First, there was an increase in the number of people who fell below the 2$-poverty line. Secondly and probably more fundamental, the poverty deficit in 2007 was greater than the deficit in 2005. This was true irrespective of which poverty line is used. Thus while the increase in the number of poor could be related to more people moving out of severe poverty, the increase in poverty deficit clearly shows increase in the depth of poverty in general. Regarding the inequality among those below the 2$- poverty line, the poverty gap squared increased by 1 percent. However, the Gini coefficient among the poor slightly decreased.

6. How dynamic is poverty in the research area?

The poverty status appears quite fluid judging from the movement into and out of poverty. While 49 percent of the very poor households remain very poor in both survey years, 33 percent of them escaped severe poverty, but still had to live on less than 2 US$ PPP per capita and day. On the other hand, 18 percent of the very poor in 2005 managed to raise their expenditures above 2 US$ PPP per capita and day. Nevertheless, there is also movement in the opposite direction. This is shown by the 23 percent of the households who moved from the category of the poor (living on less than 2 US$ per capita and day) in 2005 to the category of the very poor (living on less than 1 US$ per capita and day) in 2007. Similarly, 4.3 percent of households who were non poor in 2005 were living in severe poverty in 2007. The movement into and out of poverty reveals quite a dynamic poverty situation in the research area.

7. What are determinants of chronic/ transient poverty?

Poverty status may depend on a number of factors which may also vary across space and time. Our study shows a number of influential determinants of poverty. Large households are shown to be more at risk of being very poor - chronically and transitorily. They are also more likely to be chronically poor. Lack of access to electricity increases the probability of severe chronic and transitory poverty as well as chronic poverty. Lack of access to transportation facilities increases the probability of poverty in general. Households that lack social capital are also more likely to be chronically very poor. Improving availability of social capital for the chronically poor should therefore form a crucial for policies and projects/programs aimed at poverty reduction in the region. Access to credit facilities also reduces the probability of becoming chronically very poor. Credit access also reduces the likelihood of a household falling into chronic and transient poverty. Thus, the implementation of micro-finance schemes aiming to improve credit availability especially for the chronically (very) poor would crucially enhance poverty reduction. Remittances also have significant effect on household poverty status. Households without access to remittances from relatives are more prone to (severe) chronic poverty. Similarly, lack of opportunities to earn non-agricultural income also increases the probability to become chronically or transitorily very poor. In general, strengthening human and physical capital would improve the status of chronically (very) poor. On the other hand, the transitory (very) poor would benefit more from temporal remedies such as insurance schemes for mitigating shocks caused by droughts and floods. Such unforeseen weather shocks frequently occur in the research area.

Chapter 6 of this study addresses four additional research questions relating to deforestation by smallholder and explores the link between poverty and deforestation.

8. How much natural forest was cleared by rural households between 1999 and 2006?

Between 1999 and 2006, 53 hectares of forest were cleared by the sample households. Extrapolating from our sample to the entire population of the research area, it follows that approximately 52 km^2 of natural rainforest were cleared by rural households.

9. What crops are grown on these plots?

50% of the cleared area is dedicated to cocoa production, while on 34% of the area the subsistence crops maize and maize are grown. Often, plots are planted with maize for one or two periods, after which cocoa production is introduced.

10. Are there notable differences between socio-economic groups?

The sample showed substantial difference between the different wealth-levels. The relatively poor tend to clear more forest than the relatively wealthy households. Indeed, 31.8 percent of households in the poorest tercile cleared forests, while only 3.3 percent of those in the wealthiest tercile engaged in deforestation. While the poorest and the poor (medium tercile) mainly grow subsistence crops such as maize and dry rice on the encroached plots, relatively wealthier households mainly grow cocoa.

11. What are the influential factors determining decisions to clear natural forest?

Wealth status has a significant impact on the decision whether to clear land. Poorer households are more likely to clear forest than wealthier households. We can therefore conclude that poverty reduction in the region is crucial not only for improving peoples' livelihoods, but can also be a step towards protecting the natural rainforest. Furthermore, households with younger household heads are more likely to engage in deforestation than households with older household heads. Interestingly, we also find that presence of social capital tends to increase deforestation. Raising awareness regarding the negative consequences of deforestation should be effected through local organizations where households are engaged. We also find evidence of positive effects of property rights on natural resource protection. Household with higher share of plots secured with land titles exhibit lower probability to engage in deforestation. Property rights reforms involving fast-tracking of land titling would therefore enhance protection of natural forests. Finally, the geographical location of the household plays a crucial role. Households living in a sub-district closer to the forest boarder are more likely to clear forest than those located farther.

12. What determines the extent of forest area cleared?

In order to understand what factors determining the extent of forest area cleared, we used a tobit model. We especially assessed the marginal effects of independent variables on the conditional expected value of the dependent variable – forest area cleared. Results obtained from this analysis are quite similar to ones from the probit model regarding the determinants of the decision to clear forests. The proposed policy measures can therefore also be applied in effort to reduce the extent of forest area cleared. The only variable that had an insignificant effect on the extent of deforestation was location in the district directly bordering the forest.

In conclusion, I suggest an integrated development program for the region involving poverty reduction and forest protection. This is particularly important given the potential reverse and aggravating effect of deforestation that would lead to a vicious cycle of poverty. I also find that the regionally calibrated tool developed in this study (the indicators and their corresponding weights can be found in appendix V) can be used to assess poverty among the target population. In addressing poverty challenges in the area, it is imperative to keep in mind that there are poverty transitions. Thus poverty reduction strategies have to account for both the needs of the chronically poor and the transitorily poor. To address chronic poverty, it would be necessary to improve access to physical and human capital. For chronically poor households access to social capital and the implementation of micro-finance schemes (in terms of micro-credits) would be of great benefit. On the other hand, regionally-based insurances schemes to deal with covariate risks of floods and drought would be beneficial for the transitorily poor. Social capital plays a rather ambiguous role. While it serves to protect households from chronic poverty, it increases the probability that a household would engage in deforestation. Organizations in the region that enhance provision of social capital therefore provide appropriate avenues for creating awareness regarding the problems of deforestation (as soil degradation etc.). In future research, it would be interesting to analyze the net effect of social capital in terms of comparing its positive effect of poverty prevention against its negative effect of increasing the probability of encroachment. However, it is difficult to weight these effects. Secure tenure rights were also found to reduce the probability as well as the extent of deforestation. Fast-tracking the issuance of land titles might therefore help in reducing deforestation. Even though, the Indonesian government implements subsidy programs for the certification of land titles (PRONA), achieving tenure security is still a prevalent problem in the country (Nuryartono 2005, Klasen et al. 2010).

Our findings share some similarities, but also have differences with results from previous studies as well as strategies so far proposed with regards to development projects and programs. Chomitz et al. (2007) for example suggest assignment and enforcement of property rights in order to protect forest frontiers. Proper planning for the expansion of road infrastructure should also take into account the need to protect forest areas. Similarly, they encourage community management of watersheds and suggest development of markets for environmental services in community owned forests.

A study by Birner et al. (2006) also analyzes factors explaining the encroachment into the LLNP and emphasizes three major causes. They show that population density, availability of suitable land in the park, and the extent of area that was already cultivated at the time of the park establishment are the major determinants of encroachment. They point out that pull factors such as placing roads near the protected areas should be avoided. Furthermore, they state that agricultural development programs aimed at poverty alleviation might make encroachment attractive if protected areas provide suitable areas for income generating agricultural activities. In addition, they suggest that the existing “Community Agreements on Conservation” have a potential to alleviate poverty and protect customary rights besides conserving the forests. These agreements were negotiated between NGOs and respective communities. The agreements involve provision of development assistance at the village level in exchange for self-commitments by the villages to protect the LLNP through reduction in the extent of cultivation inside the park.

The World Bank’s Forest Strategy and Operational Policy also highlights the equality in importance of the pillars of economic development, poverty reduction, and protection of global forest values (World Bank 2009a). It is based on three independent parts (World Bank 2004a):

a) harnessing the potential of forests to reduce poverty, e.g. by fostering (marginalized) peoples participation in forest management, and by promoting sustainable forestry, community forestry, and agroforestry

b) integrating forests into sustainable economic development, e.g. by improving forest governance, and investing in environmental services

c) protecting local and global environmental values, e.g. by establishing protected areas and developing markets for international global public goods such as biodiversity.

This strategy thus follows a holistic approach that includes poverty alleviation, sustainable economic development and environmental quality. It is implemented for example, by integrating the forest sector reforms in the Poverty Reduction Strategy Papers (PRSPs). Towards this goal, the World Bank lending programs are also intensifying the integration of forest components into natural resource and rural development programs (Contreras Hermosilla and Simula 2007). However, this strategy was developed mainly for integrating forests into the World Bank programs at the macro- and sector level and not particularly for the design of programs at the micro-level.

Another framework for development projects that combines poverty reduction and protection of forest is given by the newly developed “Reducing Emissions from Deforestation and Degradation” (REDD) mechanism. It uses market/financial incentives to reduce the emission of greenhouse gases. The scheme involves developed countries providing funding to developing countries who in return commit to reduce deforestation as a means of reducing green house gases (REDD-I 2009). Other schemes for Payments for Environmental Services (PES) can also be used to simultaneously address problems of poverty and deforestation. The assessment of the effects of PES in the research area is covered in a study by Seeberg-Elverfeldt (2008, Seeberg-Elverfeldt et al. 2009).

The shortcoming of these programs, however, is that additional income might not deter people from deforestation (Zwane 2005, Chomitz et al. 2007). Zwane (2005) state for that small increases in income will not reduce the rate at which smallholder households clear land. Moreover, subsistence farmers might not be responsive to market based incentives, because they are not reached by them (Angelsen and Kaimowitz 1999).

Thus future research should further address the implementation of such a integrated project addressing equally the reduction of poverty and deforestation. Especially it should be examined how such a regional project can be linked to a more macro-level oriented framework.

6.2 Methodological conclusions

In general, a larger sample size would have helped to overcome some analytical shortcomings. For example, a more precise calibration of the poverty assessment tools (Chapter 2 and 3) would have been possible if an out-of-sample test was applied. An out-of-sample test would involve splitting a sample randomly into two parts. One of these parts would be used for the tool calibration and the second part would be used for the poverty assessment (Houssou and Zeller 2009).

The second limitation is that the sample used is only representative for the research area. Thus, policy implications such as the ones recommended in Chapter 4 may not be applicable to other parts of Indonesia without further analysis involving a national representative data. However, the advantage is that implications derived from the analysis are precisely suited to the region. This is in comparison to implications from national studies that are often not easily be broken down to specific regional scenarios. Finally, extending the panel data through additional rounds of surveys would allow for the use of the components approach in measuring poverty dynamics.

In exploring the link between poverty and deforestation, geo-referenced plot data derived from satellite images would provide more detailed information for accurate measurement of the true rate of deforestation. However, obtaining such geo-referenced data at plot-level is time-consuming and costly and was therefore not possible in the frame of this study.

The study employed two concepts of poverty measurement. Chapter 2-4 are based on an expenditure-based definition of absolute poverty, while Chapter 5 integrates relative poverty assessment. This is because the analyses in Chapter 2-4 are based on two waves of expenditure surveys, from which the actual daily per capita consumption expenditures were derived. In contrast, the analysis in Chapter 5 is based on three waves of household survey on income sources, and therefore did not contain detailed expenditure information. Furthermore, deriving per capita income from this income data would have been time consuming. In any case, expenditure measures of welfare are preferred to income income-based measures (Ravaillion 1992, Deaton 1997). Given these challenges, the study integrated a relative poverty index (Abu Shaban 2001) in the analysis carried out in Chapter 6. Based on poverty rankings, it is likely that the poorest tercile includes households falling short of the 1 US$-poverty line while the medium tercile mainly include those falling short of the 2 US$-poverty line. The upper tercile is largely expected to contain non-poor households. I cannot exactly validate this statement, because I observed the absolute poverty figures for the years 2005 and 2007, whereas the relative figures are from 2000. To correctly compare the figures the poverty index would have to be recalibrated for either 2005 or 2007. In this regard, future research should address the comparability of both poverty measures.

The data quality and the findings of this study can, however, not be understated. Panel data is generally costly to obtain and is therefore scarcely used in studies. It is thus quite remarkable that we were able to obtain a panel of expenditure data from the 2005 and 2007 surveys. Equally important was data from the income surveys: Availability of data from household surveys of the years 2000/2001, 2004 and 2006 was thus of great benefit to our study. The expenditure dataset enabled the evaluation of poverty assessment tools applied in the research are in 2005 in comparison with the poverty assessment tool provided by the IRIS Center. Additionally, the study contributes the most recent work on poverty dynamics in the Indonesian using the expenditure data. Using a sample with three observations (from the income surveys) that is located at the boarder of a national park that protects natural tropical rainforest enabled an understanding of how household characteristics in the base year (2000) determined the decision to clear forests in the subsequent years.

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Appendices

Appendices I-VIII refer to the Chapters 2 and 3. In the tables, the different poverty assessment tools estimated in 2005 and 2007 are displayed. The one, we recommend in our paper is marked grey. Appendices VII-XI relate to Chapter 4. Appendices I-XI are all based on own data. Appendix XII relates to Chapter 5. On an enclosed CD, all questionnaires used in this study are provided (appendices XIII-XX).

Appendix I: Model 1 - one-step tools 2005

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.00408	-0.0114475
Age of household head squared	0.00000381	0.0000701
Household size	-0.33943	-0.3473012
Household size squared	0.01614	0.0166068
District is Lore Utara (1=yes)	0.04269	0.2268724
District is Palolo (1=yes)	-0.01791	0.085412
District is Sigi Biromaru (1=yes)	-013092	-0.099287
District is Kulawi (1=yes)	-0.20071	-0.0603859
District is Pipikoro (1=yes)	0.18357	-0.1378501
Maximum education of any female household member is completed secondary level	0.15245	0.0520263
Number of days out of last seven days in which any of four superior foods was eaten (large fish, beef/pork/buffalo meet, chicken/duck or egg)	0.02715	0.0148052
Household ate less food for less than 10 days within the last 12 month (1=yes)	-0.18854	-0.0996536
Natural logarithm (LOG) of average clothing expenditures of household members	0.08137	0.0850004
Household feels that healthcare expenditures are above need (1=yes)	0.49722	-0.0451079
LOG, value of metal cooking pots	0.01612	0.0184119
Household agrees that people in the neighborhood are basically honest and can be trusted (1=yes)	-0.18495	-0.0915847
Household agrees that if it loses a goat or pig some body would help to look for it (1=yes)	-0.15315	0.140665
LOG, expenditures on other expenditure, social events and leisure in the last 12 month	0.03581	0.054865
Total value of received dowry in past three years	0.04136	0.0459245
LOG of annual total consumption expenditures from section C	0.33365	0.4095704
Total value of remittances sent divided by total household expenditures	0.58055	0.4633346
Total value of remittances received divided by total household expenditures	0.73297	0.6485396
Total value of transportation assets	0.02083	0.0361474
Household made a recent home improvement	0.20049	0.1401932
Constant	2.6717	0.909168
adjusted R2 / pseudo R2	0.5072	0.5092

Appendix II: Model 1 – two step coefficients 2005 (for households below the 32 predicted expenditure percentile from one-step regression)

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.03310	-0.0028064
Age of household head squared	0.00036742	0.0000395
Household size	-0.29589	-0.2479853
Household size squared	0.01626	0.0110731
District is Lore Utara (1=yes)	-0.14092	-0.027781
District is Palolo (1=yes)	-0.05193	0.0818578
District is Sigi Biromaru (1=yes)	0.09757	0.1757076
District is Kulawi (1=yes)	0.07665	0.0812342
District is Pipikoro (1=yes)	0.01262	0.1511923
Maximal education of any female household member is completed secondary level	0.21484	0.0800268
Household member lost weight because of food scarcity (1=yes)	-0.23240	-0.0809422
Food expenditure share of total consumption expenditures in percent	-0.00475	-.0005321
Household eats rice mixed with maize because of food scarcity (1=yes)	-0.21182	-0.1111202
Age of youngest household member	-0.01189	-0.0059062
Percentage of dependents younger than 18 and older than 60 (in relation to household size)	-0.00699	-0.0056768
Household head works outside of agriculture (1=yes)	0.48780	0.5538221
Trunk or suitcase ownership (1=yes)	0.18062	0.1213547
Total value of furniture sets owned by household	0.02239	0.0277311
Household agrees that people in the neighborhood are basically honest and can be trusted (1=yes)	-0.17190	-0.2547795
In the last three years household borrowed money from informal market (1=yes)	0.92374	0.6022479
Natural logarithm (LOG) of annual total consumption expenditures from section C	0.27978	0.25574
Total value of transportation assets	0.08589	0.084441
Household made a recent home improvement (1=yes)	0.21363	0.1821874
Exterior walls are brick or stone (1=yes)	0.38801	0.2989028
Constant	5.22946	4.426052
adjusted R2 / pseudo R2	0.6922	0.3704

Appendix III: Model 1 – one step tools 2007

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.00823	-0.0186433
Age of household head squared	0.00003415	0.0001231
Household size	-0.20166	-0.2665021
Household size squared	0.00559	0.0099218
District is Lore Utara (1=yes)	-0.05399	-0.2644595
District is Palolo (1=yes)	0.02162	-0.1532885
District is Sigi Biromaru (1=yes)	0.12894	-0.0767895
District is Kulawi (1=yes)	-0.17071	-0.3706525
District is Pipikoro (1=yes)	-0.46834	-0.6038181
Number of children in school age 6-16	-0.04397	-0.0457086
Household purchases rice monthly (1=yes)	0.17070	-0.1965804
Household members always ate enough of what they wanted (1=yes)	0.14326	0.0645585
Household ate less food for more than 10 days within the last 12 month (1=yes)	-0.30615	0.2039448
Household head has no education (1=yes)	-0.18206	-0.1920354
Household ate broken rice because of food scarcity (1=yes)	-0.26031	-0.0827068
Percentage of dependents younger than 15 and older than 64 (in relation to household size)	-0.00369	-0.0018248
Bucket ownership (1=yes)	0.15307	0.0755459
Family member work some were else and sends money (1=yes)	0.33000	0.358551
Satellite dish ownership (1=yes)	0.18122	0.1885153
Ntural Logarothm (LOG) of annual total consumption expenditures from section C	0.32418	0.4083332
Number of metal cooking pots owned	0.02608	0.0248546
LOG of value of major funds and assests inherited since last survey	0.04324	0.0462334
Total size of rooms in the house in m^2	0.00256	0.0021805
Main entrance door has no lock (1=yes)	-0.11018	-0.1586526
Constant	4.32357	3.563731
adjusted R2 /pseudo R2	0.5497	0.4568

Appendix IV: Model 1 – two step coefficients 2007 (for households below the 55 predicted expenditure percentile from one-step)

Indicators	OLS coefficients	Quantile coefficients
Age of household head	0.03236	-0.0030931
Age of household head squared	-0.0003426	-0.000035
Household size	-0.16895	-0.1889197
Household size squared	0.00479	0.0048631
District is Lore Utara (1=yes)	-0.42941	-0.3443644
District is Palolo (1=yes)	-0.22750	-0.1335386
District is Sigi Biromaru (1=yes)	-0.33756	-0.2557269
District is Kulawi (1=yes)	-0.40052	-0.3073451
District is Pipikoro (1=yes)	-0.59172	-0.5412928
Number of children in school age 6-16	-0.04134	-0.0128722
Household feels that education expenditures are below need (1=yes)	-0.09278	-0.0933938
Ntural logarithm (LOG) of expenditures for education in the last 12 month (lnc07)	0.01677	0.0142231
Household head has no education (1=yes)	-0.09311	-0.0600794
Number of household members with completed secondary education	0.07882	0.0808567
Household ate less food for more than 10 days within the last 12 month (1=yes)	-0.30665	-0.0552918
In the last 7 days household ate only plain rice with chilly (1=yes)	-0.04989	-0.2209765
Household ate broken rice because of food scarcity (1=yes)	-0.33938	-0.1253737
Household uses cooking fuel other than collected wood (1=yes)	0.20249	0.4508306
Household head works as wage labourer in agriculture (1=yes)	0.13801	0.2116596
LOG of monthly expenditures on transport	0.03283	0.0269307
Number of beds owned	0.03890	0.0318785
LOG of value of major funds and assests inherited since last survey	0.04191	0.0466164
Total number of rooms of the house	0.03760	.0500705
Number of organizations any household member is participating in	0.02781	0.0353858
Constant	8.06871	8.867761
R2 adjusted/ pseudo R2		0.3220

Appendix V: Model 2 – one-step tools 2005

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.02092	-0.0086289
Age of household head squared	0.00018150	0.0000894
Household size	-0.33009	-0.3151942
Household size squared	0.01557	0.0147289
District is Lore Utara (1=yes)	-0.14250	0.0317548
District is Palolo (1=yes)	-0.39967	-0.187318
District is Sigi Biromaru (1=yes)	-0.75771	-0.3486859
District is Kulawi (1=yes)	-0.54191	-0.1762002
District is Pipikoro (1=yes)	-0.51655	-0.0444193
Total number of rooms in the house	0.05019	0.0784546
Metal cooking pots ownership (1=yes)	0.19478	0.1942551
Clock ownership (1=yes)	0.14010	0.2413234
VCD-Recorder ownership (1=yes)	0.31491	0.3156017
Motorcycle ownership (1=yes)	0.20235	0.3250668
Cow ownership (1=yes)	0.21482	0.2015923
Household use cooking fuel other than collected wood (1=yes)	0.20555	0.2945647
Toilet is personal pit toilet (1=yes)	-0.27415	-0.2767342
Water from well in residence yard (1=yes)	0.16186	0.0663461
Household head sleeps in bed with thin mattress made out of fibres (1=yes)	-0.22723	-0.0300095
Household cooks in separate kitchen (1=yes)	-0.30423	-0.2721108
Household has own or shared electricity (including generator) (1=yes)	0.13892	0.2058736
Percentage of dependents younger than 18 and older than 60 (in relation to household size)	-0.00326	-0.004406
Household made a recent home improvement (1=yes)	0.22777	0.1899791
Number of trunks and suitcases owned	0.10318	0.0160496
Constant	10.42384	9.279638
adjusted R2 / pseudo R2	0.5564	0.4372

Appendix VI: Model 2 – two step coefficients 2005 (for households below the 38 predicted expenditure percentile from one-step regression)

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.01925	-0.0421594
Age of household head squared	0.00030142	0.0004449
Household size	-0.31577	-0.1822189
Household size squared	0.01277	0.0061047
District is Lore Utara (1=yes)	-0.15643	-0.0516643
District is Palolo (1=yes)	-0.02480	0.0007364
District is Sigi Biromaru (1=yes)	-0.05451	-0.036378
District is Kulawi (1=yes)	0.16696	0.0849417
District is Pipikoro (1=yes)	-0.06546	-0.0282016
Total number of rooms in the house	0.10367	-.0882637
Stove ownership (1=yes)	0.23041	0.2278252
Bicycle ownership (1=yes)	0.35890	0.3464673
Motorcycle ownership (1=yes)	0.71038	0.5439219
Cow ownership (1=yes)	0.47001	0.1174882
Number of chicken owned	0.01453	-0.0115196
Lock of main entrance door is padlock (1=yes)	0.18133	0.0065311
Exterior walls are brick or stone (1=yes)	0.19609	0.2160675
Light source: electricity with shared connection (1=yes)	-0.24055	-0.1676745
Household cooks in separate kitchen (1=yes)	-0.28469	-0.228172
Household head works outside of agriculture (1=yes)	0.46073	0.1679816
Toilet is shared (pit toilet or improved latrine) (1=yes)	-0.22737	-0.1945254
Age of youngest household member	-0.02201	-0.0129163
Ratio of dependents younger than 18 and older than 60	-0.13247	-0.1550794
Household uses other cooking fuel than collected wood (1=yes)	0.71309	0.5847601
Constant	9.29888	9.585162
adjusted R2 / pseudo R2	0.6619	0.2585

Appendix VII: Model 2 – one-step tools 2007

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.02033	-0.0393753
Age of household head squared	0.00011968	0.0002928
Household size	-0.13034	-0.1817033
Household size squared	0.00683	0.0090966
District is Lore Utara (1=yes)	0.20392	0.1881199
District is Palolo (1=yes)	0.27159	0.3648901
District is Sigi Biromaru (1=yes)	0.35094	0.3670464
District is Kulawi (1=yes)	-0.03539	0.0186634
District is Pipikoro (1=yes)	-0.15451	-0.0257288
Total number of rooms in the house	0.04898	0.0636539
The size of rooms in m^2	0.00270	0.0030044
Bucket ownership (1=yes)	0.16562	0.1687359
Satellite dish ownership (1=yes)	0.20995	0.1786086
Motorcycle ownership (1=yes)	0.19675	0.1687359
Cow ownership (1=yes)	0.15433	0.1466964
Number of beds owned	0.07100	0.0731356
Household uses cooking fuel other than collected wood (1=yes)	0.19517	0.276345
Main entrance door has no lock (1=yes)	-0.17058	-0.1942297
Exterior walls are brick and stone (1=yes)	0.17873	0.2743887
Floor of dwelling is cement with cover (ceramic etc.) (1=yes)	0.12446	0.0894297
Total number of females in the household	-0.08032	-0.0348353
Number of dependents younger than 18 and older than 60	-0.09213	-0.0961513
Number of metal cooking pots owned	0.03273	0.0382189
Number of trunks and suitcases owned	0.13866	0.2350127
Constant	9.23287	9.620885
adjusted R2 / pseudo R2	0.4819	0.3925

Appendix VIII: Model 2 – two step coefficients 2007 (for households below the 44 predicted expenditure percentile from one-step)

Indicators	OLS coefficients	Quantile coefficients
Age of household head	-0.04837	-0.0405059
Age of household head squared	0.00037032	0.0002889
Household size	-0.09691	-0.0306308
Household size squared	0.00119	-0.0006767
District is Lore Utara (1=yes)	-0.09093	0.2709539
District is Palolo (1=yes)	0.03681	0.4307205
District is Sigi Biromaru (1=yes)	-0.12798	0.3320356
District is Kulawi (1=yes)	-0.19439	0.0605613
District is Pipikoro (1=yes)	-0.18528	0.0736346
Total number of rooms in the house	0.07169	0.1147784
Number of furniture sets owned	0.05935	0.1028159
Bicycle ownership (1=yes)	0.08210	0.125419
Number of stoves owned	0.05935	0.0191933
Cow ownership (1=yes)	0.25583	0.3179476
Chicken ownership (1=yes)	0.15217	0.0979627
Refrigerator ownership (1=yes)	0.54052	0.5163564
Number of bulls owned	0.14699	0.155838
Number of trunks and suitcases owned	0.15239	0.1411559
Number of metal cooking pots owned	0.05394	0.065624
Household head works outside of agriculture (1=yes)	0.29686	0.2342386
The size of rooms in m^2	0.00221	0.003971
Number of dependents younger than 18 and older than 60	-0.02463	-0.1399493
Floor of dwelling is earth or bamboo (1=yes)	-0.13569	0.0031705
Household uses cooking fuel other than collected wood (1=yes)	0.32110	0.4179697
Constant	9.73820	8.940112
adjusted R2 / pseudo R2		0.3223

Appendix IX: The development of three different poverty lines for Central Sulawesi between 2005 and 2007

	1 $US	National (rural)	2 $US
2005	2723	3920	5446
2007	3436	4935	6872

Appendix X: First differences – True variance in data and the influence of covariate shocks

Dependent variable	Natural logarithm (ln) of expenditure in year 2007 minus ln of expenditure in year 2005		
	Model 1	**Model 2**	**Model 3**
Change in ln of household (hh) size	-1.035407 (-4.76)***	-1.018646 (-4.45)***	-0.9753974 (-3.91)***
Change in the number of female adults	0.1194745 (1.33)	0.1184379 (1.29)	0.1094855 (1.15)
Change in the number of male adults	0.1270705 (1.33)	0.1289336 (1.33)	0.1280342 (1.34)
Change in the dependency ratio (people younger than 15 and older than 64)	0.0017196 (0.43)	0.0011099 (0.26)	0.0007405 (0.16)
Change in ownership status of furniture sets	0.229877 (1.49)	0.2308801 (1.51)	0.2447406 (1.64)
Change in ownership status of televisions	0.3542954 (1.62)	0.3215747 (1.44)	0.3264717 (1.43)
Change in natural logarithm (ln) value of animal owned	0.0079149 (0.43)	0.0064107 (0.35)	0.0091016 (0.48)
Change in ln of transportation assets owned	0.0292342 (1.67)*	0.0343303 (2.01)**	0.0383566 (2.22)**
Change in count of persons with completed primary education	0.0682336 (1.36)	0.0506388 (1.12)	0.0541374 (1.06)
Change in count of persons with completed secondary education	-0.1060268 (-1.31)	-0-.1194007 (-1.46)	-0.1321655 (-1.58)

Note: The numbers in parentheses are t-values; * Significant at the 10 percent level, ** Significant at the 5 percent level; *** Significant at the 1 percent level; [a] in contrast to kecamatan Sigi Biromaru

Appendix X continued: First differences – True variance in data and the influence of covariate shocks

Dependent variable	Natural logarithm (ln) of expenditure in year 2007 minus ln of expenditure in year 2005		
	Model 1	**Model 2**	**Model 3**
Change in size of homestead are	-0.0036296 (-0.78)	-0.0040727 (-0.84)	-0.0041658 (-0.84)
Change in size of irrigated ricefields	.0021079 (1.62)*	0.0019848 (1.58)	0.0020735 (1.66)*
Change in size of upland area	-0.0000814 (-0.18)	-0.0000241 (-0.05)	-0.000059 (-0.12)
Change in size of lowland area	0.0005838 (0.65	0.000394 (0.42)	0.0002794 (0.29)
Change in size of other land	0.0001006 (0.08)	0.000079 (0.07)	-0.0001789 (-0.15)
Constant	-0.1402143 (-2.88)***	-0.0398902 (-0.48)	0.0571324 (0.41)
Kecamatan Lore Utara[a] (1=yes)	-	-0.3432928 (-2.67)***	Replaced by 12 village dummies
Kecamatan Palolo[a] (1=yes)	-	-0.0655161 (-0.49)	
Kecamatan Kulawi[a] (including village Lawe) (1=yes)	-	-0.1248839 (-1.17)	
Joint significance of covariates	F= 3.84***	F= 3.90***	F= 2.94***
R2	0.23	0.26	0.27

Note: The numbers in parentheses are t-values; * Significant at the 10 percent level, ** Significant at the 5 percent level; *** Significant at the 1 percent level; [a] in contrast to kecamatan Sigi Biromaru

Appendix XI: Six severe impoverished households: Searching for causes of their pauperization

Variables*	Household (Hh) 1		Hh 2		Hh 3		Hh 4		Hh 5		Hh 6	
	2005	2007	2005	2007	2005	2007	2005	2007	2005	2007	2005	2007
Luxfood	6	3	4	1	5	4	1	2	3	3	3	1
Chicken	0	1	0	1	1	1	0	0	0	1	1	1
Nchicken	0	6	0	8	4	60	0	0	0	10	1	32
Totarea	118	68	53	28	610	750	?	750	125	75	3	18
Occup	1	1	1	1	1	1	1	1	1	2	1	1
Hhsize	5	5	4	7	6	4	5	7	6	7	6	6
Dep15t64	40	60	25	28.6	50	50	60	71.4	66.7	57.1	50	50

*Explanation of variables in appendix XI:

Luxfood: Number of days in week prior to interview any of four luxury foods (big fish/meat of bull, cow, pig/chicken,duck or egg) was eaten

Chicken: Dummy for chicken ownership, 1= yes, 0= no

Nchicken: number of chicken owned

Totarea: total area of land owned in are

Occup: occupation of household head, 1= farmer, 2= causal worker in agriculture

Hhsize: Household size

Dep15t64: dependency ratio of children younger than 15 and elderly older than 64 in relation to households size

Appendix XII: Component matrix for the relative poverty assessment tool

Indicators	Component loading*	
	1a	2b
Asset related indicators		
Total value of electronic appliances owned	0.717	-0.389
Thotal value of transportation assets owned	0.632	-0.455
Number of televisions owned	0.674	0.456
Housing quality related indicators		
Type of electricity connection (ordinal)	0.719	-0.26
Type of wall (ordinal)	0.568	-0.369
Type of roof (ordinal)	0.67	0.438
Type of floor (ordinal)	0.616	0.511
Food and consumption related indicators		
Number of days with food shortage in the last 12 month	-0.328	0.111
Share of income spent on food out of a hypothetical additional income of 20,000 IDR per week	-0.448	0.302
Per capita expenditures on clothes and footwear during the last 12 month	0.685	0.314

Source: Abu Shaban (2001)

Note: *extraction method: Pricipal Component Analysis, 2 compnents extracted; [a] explains 38.22% of the variance (was taken for poverty assessment); [b] explains 14.33% of the variance

Appendix XIII (on an enclosed CD): Benchmark questionnaire 2005 (English version)

Appendix XIV (on an enclosed CD): Composite questionnaire 2005 (English version)

Appendix XV (on an enclosed CD): Benchmark questionnaire 2007 (English version)

Appendix XVI (on an enclosed CD): Composite questionnaire 2007 (English version)

Appendix XVII (on an enclosed CD): Household questionnaire 2000 (English version)

Appendix XVIII (on an enclosed CD): Household questionnaire 2001 (English version)

Appendix XIX (on an enclosed CD): Household questionnaire 2004 (English version)

Appendix XX (on an enclosed CD): Household questionnaire 2006 (English version)