College of Development Studies

Center for Environment and Development Studies

Forest Cover Changes and Household Energy Utilization Patterns in the Semien Mountains and Adjacent Districts, Northwest Ethiopia

Belete Debebe Tekle

A Dissertation Submitted to Center for Environment and Development Studies, College of Development Studies

Presented in Fulfilment of the Requirement for the Degree of Doctor of Philosophy in Development Studies (Environment and Development Studies)

Addis Ababa University,

Addis Ababa, Ethiopia

July 2023

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DECLARATION

DECLARATION

I, the undersigned, declare that this is my original work, has never been presented in this or any other university, and that all the resources and materials used for the dissertation have been fully acknowledged.

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This dissertation has been submitted for examination with my approval as university supervisor.

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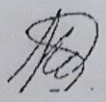
Signature: 

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APPROVAL SHEET

APPROVAL SHEET

This is to certify that the thesis prepared by **Belete Debebe** entitled "**Forest Cover Changes and Household Energy Utilization Patterns in the Semien Mountains and Adjacent Districts, Northwest Ethiopia**" has been submitted for the fulfilment of the requirement for the Degree of Doctor of Philosophy (Environment and Development Studies) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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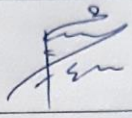
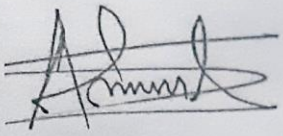
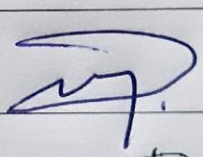
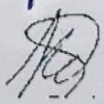
Dr. Engedawork Assefa (Assoc. Prof.) **Chairman**		14.07.23
Dr. Agena Anjulo **External Examiner**		14/07/2023
Dr. Desalegn Wana **Internal Examiner**		14/07/2023
Professor Feyera Senbeta **Principal Supervisor**		13/07/2023
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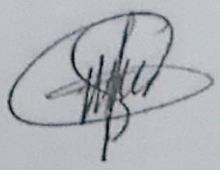
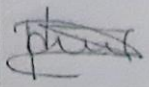
Dr. Ermias Teferi (Assoc. Prof.) **Co-Supervisor**		14/07/2023
Dr. Dawit Diriba **Co-Supervisor**		13/07/2023

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LIST OF PUBLICATIONS

The following articles are extracted from the thesis. Some of them were published in journals; the third article was accepted for publication, and the last one is under review.

Article 1:

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Article 2:

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Article 3:

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Article 4:

Debebe, B., Senbeta, F., Teferi, E., Diriba, D., Teketay, D., & Tegegne, AD. Fuelwood Collection and Children's School Attendance: Evidence from Northwest Ethiopia (Under review). Education Sciences Journal.

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ABBREVIATIONS

ANRS	Amhara National Regional State
AWF	African Wildlife Foundation
BOFED	Bureau of Finance and Economic Development
CCT	Control Cooking Test
CRGE	Climate Resilient Green Economy
CSA	Central Statistical Agency
EFAP	Ethiopian Forestry Action Program
EWCA	Ethiopian Wildlife Conservation Authority
FAO	Food and Agricultural Organization
FDRE	Federal Democratic Republic of Ethiopia
GDP	Gross Domestic Product
GIS	Geographic Information System
IAP	Indoor Air Pollution
ICS	Improved Cooking Stoves
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
KIIs	Key Informant Interviews
KPT	Kitchen Performance Test
LC	Land Cover
LPG	Liquid Petroleum Gas
LULC	Land Use and Land Cover
MEFCC	Ministry of Environment, Forest and Climate Change
MoWE	Ministry of Water and Energy
MVP	Multivariate Probit Model
NBE	National Bank of Ethiopia
OLS	Ordinary Least Square
PRB	Population Reference Bureau
SAE	Standard Adult Equivalent
SD	Standard Deviation
SDGs	Sustainable Development Goals
SMNP	Semien Mountains National Park
SSA	Sub-Saharan Africa
UNDP	United Nations Development Program
UNEP	United Nations Environment Program
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNSD	United Nations Statistics Divisions
WB	World bank
WBT	Water Boiling Test
WHO	World Health Organization

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Forest Cover Changes and Household Energy Utilization Patterns in the Semien Mountains and Adjacent Districts, Northwest Ethiopia

ABSTRACT

Forests are a major source of domestic energy in many developing countries, including Ethiopia. Energy is a cornerstone and strategic tool to meet basic human needs and address many global development challenges. However, the current use patterns of forests have resulted in deforestation, which is resulted in jeopardizing the energy supply for households. This study aims to investigate forest cover changes and household energy utilization patterns in the Semien Mountains and adjacent districts of Northwestern Ethiopia. The study used exploratory sequential mixed methods. This study was based on data generated from 420 randomly selected households in two districts using household surveys, key informant interviews and field observation. The study (i) quantify forest cover changes using remotely sensed satellite data and identify the drivers of change through socio-economic surveys and key informant interviews, (ii) examines the determinants of household fuel choice for domestic chores using a multivariate probit model, (iii) measures the effectiveness of Mirt improved stove using kitchen performance test and analyse the determinants of adoption of Mirt stove using logistic regression model and (iv) examines the link between fuelwood collection and children's school attendance using a two-stage conditional maximum likelihood estimation technique. The results revealed that the percentage area under forests declined by about 31% over the last 36 years. This loss translates to an annual average forest loss of about 1.02% (919 ha year^{-1}). The observed reduction in forest cover was mainly driven by many intertwined factors, including the growing demand for domestic energy needs and farmland expansion. The change detection matrix revealed that forests lost the most (65,898 ha). Moreover, the spatial patterns of change revealed that forest cover experienced both swap and net change. The results also showed household energy utilization patterns skewed to biomass fuels, particularly fuelwood, resulting in deforestation. Estimates of the multivariate probit model showed that a mix of socio-economic factors determines household cooking energy choice behaviour. The study also found evidence of fuel stacking, as there is an increase in the number of fuel types used by households as socio-economic status improves. Besides, the kitchen performance test results revealed that Mirt stoves saved household fuelwood consumption by 777 kg per household per year. Similarly, Mirt stove reduced the time needed to bake injera compared to three-stone stoves by 23.5 minutes per baking session, equivalent to an annual per capita time-saving of about 56.4 hours. Empirical results highlighted that household age, sex, education, family size, availability of kitchens and access to credit have significant influences on the decision to adopt Mirt stove. Furthermore, the finding revealed that children involved in fuelwood collection tasks reduce the likelihood of school attendance. The results support the hypothesis of a negative relationship between children participating in fuelwood collection work and the likelihood that they will attend school. Thus, the study suggests that a concerted policy effort is required to help the local community use biomass fuels more environmentally friendly and use sustainable and affordable modern energy sources through access to improved cookstoves and afforestation to increase biomass supply.

CHAPTER ONE: INTRODUCTION

1.1. Background

Forests are among the world's most productive land-based ecosystems in which trees are the dominant (UN, 2017). They cover one-third of the global land surface and are crucial to life on Earth, human well-being, sustainable development and the health of the planet (Köhl et al., 2015; FAO, 2017; UN, 2017; Katila et al., 2020). Forests provide a wide range of benefits ranging from local livelihoods and socioeconomic development to ecological services (Vedeld et al., 2007; Garedew, 2010; Köhl et al., 2015; Duguma et al., 2019; Katila et al., 2020). Forests are also vital for watershed protection and biodiversity conservation (Käyhkö et al., 2011; Miura et al., 2015), carbon sequestration and climate regulation (Wambua, 2011; Addo-Fordjour & Ankomah, 2017; Lossou et al., 2019), habitat for wildlife (Deka et al., 2018), contributing to food security (Gbetnkom, 2008), and sources of domestic energy (Arnold et al., 2006; Katila et al., 2020). In this sense, as MacDicken et al. (2015) and Munang et al. (2011) reckon, it is difficult to think of individuals that do not depend on forests and forest products and services for at least part of their livelihood and well-being in some way. People-forest interactions, however, vary across space and time due to variations in ecological, social and economical factors on the ground (Katila et al., 2020).

Despite the critical role of forests in supporting life on Earth, sustainable development and human well-being, global forest area is declining dramatically (UN, 2017). It is estimated that between 1990 and 2020, global forest cover decreased from 32.5% to 30.8%, representing a net loss of 178 million ha of forests (FAO, 2020; FAO and UNEP, 2020). It is predicted that global forest cover is projected to continue to decline at alarming rates (D'Annunzio et al., 2015), resulting in the impoverishment of the environment and losses of livelihoods (Käyhkö et al., 2011).

Deforestation and forest degradation are the results of either proximate/direct or underlying/indirect drivers (Geist & Lambin, 2001). Indirect drivers encompass complex interactions of fundamental political, socioeconomic, cultural, and demographic trends, as well as technological processes, whereas direct drivers include anthropogenic activities or immediate actions that have a direct impact on forest covers: agriculture, urban expansion, mining, livestock grazing and forest fires (Rotich & Ojwang, 2021). The underlying causes determine the degree of direct causes resulting in forest cover change (D'Annunzio et al., 2015).

Overall, the highest percentage of annual forest loss was reported in the tropics (5.5 million ha per year), particularly in Sub-Saharan Africa (SSA) (FAO, 2020). The imprudent use of forests has also led locally to manifold socio-economic and ecological problems, including food insecurity and poverty, loss of biodiversity and genetic resources, disturbance of microclimates, loss of wildlife resources, and shortage of fuelwood (Gbetnkom, 2008; Hu et al., 2014; Keenan et al., 2015; UN, 2017; FAO and UNEP, 2020). The change in forest cover further affects many aspects of human well-being, in particular, poor people who often directly depend on forest products (Ahammad et al., 2019).

Forests also play a crucial role in the global supply of energy services (Bandyopadhyay et al., 2011). A crucial link between forests and sustainable development has been recognized in the Sustainable Development Goals (SDGs). The role of forests in ensuring access to reliable, affordable, sustainable and modern energy for all immensely great - the overarching objective of the SDGs-7 (Jagger et al., 2019). Sustainable energy development requires a long-term supply of energy sources that are readily and sustainably available at a reasonable cost and can be utilized for all required tasks without causing negative societal and environmental impacts (Sopian et al., 2011). Modern and efficient energy services help reduce strain on forest resources and can play a critical role in improving children's educational opportunities. Therefore, access to sustainable energy services is essential to sustainable development (Sehjpal et al., 2014).

It is estimated that over 2.7 billion people in the developing world burn biomass fuels, primarily fuelwood, to meet their domestic energy needs (IEA, 2017). The persistence of biomass fuels is partially due to the slow development in the market for modern fuels and efficient cookstoves (Malla & Timilsina, 2014). In addition, high capital costs combined with poor infrastructure further inhibit the adoption of modern fuels and technologies (Jagger & Kittner, 2017). The heavy reliance on biomass fuels, on the other hand, does pose not only a major threat to environmental sustainability but also a health hazard, as smoke from combustion contributes to indoor air pollution (Heltberg, 2005; Ekholm et al., 2010; Han et al., 2018). Women and children are reportedly exposed to pollution from indoor cooking smoke on a daily basis since they spend a large amount of time near cooking fires (Ifegbesan et al., 2016). Additionally, fuel collection is mostly carried out by women and children (Casteleyn, 2017), which prevents them from generating income and pursuing their education (Lewis & Pattanayak, 2012). To reduce these adverse effects, it is crucial to initiate universal access to efficient and sustainable energy services.

As in other developing countries, forests are vital to the livelihoods of millions of Ethiopians and the national economy (Teketay, 2001). Forest provides numerous products and services, including food, fodder, medicine, fuelwood, income, clean water, erosion control, regulating climate change, and safeguarding fragile landscapes (Dessie, 2007; Babulo et al., 2009; Gobeze et al., 2009; Ayana, 2014; Tadesse et al., 2015; Zegeye, 2017; Belayneh et al., 2018; FDRE, 2018; Duguma et al., 2019; Negassa et al., 2020). Securing the livelihoods of the growing population of the country is inseparably linked to the exploitation of forest resources (Baye, 2017). These forest products serve mainly as an 'intermediate' input into a household production process (Bandyopadhyay et al., 2011). However, despite the contribution of the forestry sector to the well-being of the people and the country as a whole, Ethiopia's forests are declining both in size (deforestation) and quality (degradation) (Bishaw, 2001; Teketay, 2001; Gobeze et al., 2009; Tadesse & Teketay, 2017; Young et al., 2020).

In Ethiopia, large population heavily rely on forests for subsistence and settlements are typically located near and/or within forests, resulting in rapid forest cover changes, therefore, people-forest interaction is substantial (Lemenih & Kassa, 2014). This has accelerated deforestation in many parts of the country. Ethiopia has diverse forest resources; however, relevant data on forest cover are scarce, and existing knowledge is incomplete and contentious (Dessie, 2007). As estimated by Pohjonen & Pukkala (1990), at the turn of the 20th century, forests covered about 40% of Ethiopia’s land mass and 90% of the highlands (>1500 m). However, it fell to 16% in the 1950s and then 2.7% in the 1990s (EFAP, 1993). Recently, Ethiopia’s forest cover has been reported to be 11% (FAO, 2010a), but it remains controversial between experts and politicians.

Some argue that forest clearance and regeneration occurred sporadically until the 20th century, after which deforestation became much more pronounced. However, reliable and consistent data on deforestation are scarce, and various sources have reported varying figures. For instance, Pohjonen & Pukkala (1990) reported that the annual rate of deforestation was about 800,000 ha year^{-1} during the 1950s, 163,000 ha year^{-1} between 1986 and 1990 (Reusing, 1998), and 141,000 ha year^{-1} between 1990 and 2010 (FAO, 2010a). The difference in estimates of deforestation is attributed to the fact that much of the information is derived from indirect sources and not from quantitative empirical studies (Bewket, 2003). Thus, the gains and losses of forest cover vary over time and need location and time-specific studies to support policies and decisions to conserve, protect and sustainably manage forests.

In Ethiopia, among the various driving forces of deforestation is the pressure from a growing population which uses forests for energy and other domestic uses (Aerts et al., 2002; Faye, 2003; Bewket, 2005; Damte & Koch, 2011; Gwavuya et al., 2012; Guta, 2014). Some authors question the link between fuelwood use and deforestation. According to Arnold et al. (2003), fuelwood supplies are often a by-product of forest clearance for agriculture and other purposes. They argued that since most fuelwood comes from trees and shrubs growing outside forest areas, fuelwood collection cannot be considered the primary cause of deforestation. In contrast, empirical evidence suggests a link between fuelwood consumption and deforestation, particularly in developing countries, where most people rely heavily on biomass energy from forests for cooking (Bandyopadhyay et al., 2011). Ethiopia's Government also believes fuelwood collection for household energy supply is one of the leading causes of deforestation (Damte, 2011). Thus, Ethiopia is confronted with a two-edged sword: escalating prices of fossil fuel and its associated greenhouse gas emission and deforestation caused by the overexploitation of forest for domestic energy demands (Tucho & Nonhebel, 2015; Mondal et al., 2017; Mondal et al., 2018).

In Ethiopia, reliable data on the extent of fuelwood use is lacking. According to Admasu et al. (2013) and Negash & Kelboro (2014), fuelwood alone accounts for nearly 80% of household energy needs, mainly harvested from natural forests and woodlots. The pressure on the forests in Ethiopia has been increasing due to the heavy reliance on fuelwood for domestic energy supply and the on-going demographic, socioeconomic, and environmental changes in the country (Scheurlen, 2015). Between 1990 and 2015, for instance, Ethiopia lost 17.3% (> 2.6 million ha) of forest cover (FAO, 2015), and fuelwood collection played a vital role in this process (FAO, 2010a). Therefore, substituting fuelwood with modern and efficient technologies can reduce pressure on forests because modern and energy-efficient technologies do not cause forest loss and degradation (Heltberg et al., 2000). But, modern energy sources are generally expensive and hardly available (Dresen et al., 2014).

An effective strategy to reduce deforestation, fuelwood scarcity, fuelwood collection time, cooking time and health problems associated with indoor air pollution is the introduction and distribution of improved cookstoves (ICS) (Megen Power, 2008; Marie et al., 2021). Adoption of ICS improves energy efficiency and mitigates the adverse environmental, economic and health impacts of biomass fuel use (Beyene & Koch, 2013; Dresen et al., 2014; Gizachew & Tolera, 2018). Despite the multiple benefits of ICS, adoption remains very low in Ethiopia and the Amhara National Regional State (ANRS) due to various socioeconomic,

cultural and institutional barriers (Kassa et al., 2020). Therefore, identifying the major bottlenecks in the transition to more efficient household energy is critical for designing environmentally benign and sustainable energy alternatives.

Households in Ethiopia lack readily available energy sources and rely heavily on self-collected fuel to meet their daily fuel needs (Gebru & Bezu, 2013). Most of the collection burden falls on women and children, particularly school-aged children, spending many hours each week collecting fuelwood for cooking (Admassie, 2003). When fuelwood becomes scarce as a result of deforestation, women and children are forced to travel long distances, which takes substantial time and labour (Dimoso, 2009; Gebru & Bezu, 2013). As reported by Cundale et al. (2017) and Beyene et al. (2014), in Sub-Saharan Africa (SSA), the time spent for collecting fuelwood ranges from 4 to 15 hours per week, depending on the availability of forest in the nearby villages. As a result, children at prime school attendance age routinely collect fuelwood for at least as many hours as adults (Ndiritu and Nyangena, 2011).

In fuelwood collection tasks, children are more valuable than adults, thereby increasing their value (Aggarwal et al., 2001; Winkler-Dworak, 2004). This task, however, reduces children's school attendance, study time, and, ultimately, their ability to learn and progress through school (Levison et al., 2018), which has detrimental effects on future human capital development (Koissy-Kpein, 2012). Empirical studies conclude that the scarcity of fuelwood leads to an increase in the amount of time children spend collecting fuel, which, in turn, negatively impacts their school attendance (Gebru & Bezu, 2013; Beyene et al., 2014). Thus, understanding forest cover changes and its implication on household energy utilization patterns and children's school attainment is crucial for developing effective policies and programs to make future interventions in the area of forests, energy and education.

1.2. Problem Justification

Forests are critical to economic growth, employment and environmental sustainability of Ethiopia (Babulo et al., 2009; Solomon et al., 2018; Negassa et al., 2020). Despite these benefits, they are constantly threatened by multifaceted and dynamic processes (Bewket, 2003; Assefa & Bork, 2014). Deforestation and forest degradation, mainly clearing forests for household energy needs, remain a primary concern in Ethiopia as well as the study area (EFAP, 1993). However, reliable data on forest cover changes have not been well-documented and quantified in a biodiversity hotspot area of high-altitude forests in the

Semien Mountains. The Semien Mountains, characterized by a wealth of biodiversity and ecosystem services, have global and local significance (Jacob et al., 2017). However, its forest resources are constantly under increasing threat due to people's dependence on forests for energy consumption as well as forest products for livelihoods and incomes (ANRS, 2007). Yet, information on changes in spatiotemporal patterns of forest cover is limited in the study area. Thus, understanding forest cover changes and their drivers necessitates time and location-specific studies using an integrated research approach.

In Ethiopia, nearly 75 million people rely on forests for household energy, livelihood, employment, and income generation (Danyo et al., 2017). Forests are essential sources of energy in Ethiopia (Teketay, 2001). Energy is a prerequisite for human survival, development and economic well-being (Salerno et al., 2010). It deeply influences all aspects of human welfare, including health care, education, job creation, access to water, agricultural productivity, and environmental sustainability (Woubishet, 2009; Tessema et al., 2014; Mengistu et al., 2016; Berhanu et al., 2016; Shallo et al., 2020; Nikus & Wayessa, 2021). However, not everyone has access to the required energy, whether traditional or modern. Most development goals, including the SDGs, cannot be met without access to sustainable, reliable and affordable fuels (UNDP, 2009; Bull, 2018). Thus, access to modern and reliable energy services is a prerequisite for unlocking economic development and improving health, education, food security, agricultural practices and gender equality (IEA, 2020). Although Ethiopia faces many challenges, one of the most critical is supplying affordable and sustainable eco-friendly renewable energy services.

Ethiopia, with a population of 115 million in 2020, is Africa's second most populous country, next to Nigeria (PRB, 2020). Although Ethiopia remains a low-income country, its Gross Domestic Product (GDP) growth of 8.3% per annum makes it one of the fastest-growing economies in the SSA countries (IEA, IRENA, UNSD, WB, 2020). As a result, a substantial increase in the energy requirements of the country (NBE, 2020). However, low access to modern and clean energy remains a significant hurdle for the Government's ambition to reach the low-middle-income status by 2025 (Pappis et al., 2021).

Ethiopia is potentially endowed with a variety of renewable and non-renewable energy resources, including hydropower, geothermal, wind, biomass as well as solar energy. However, these have not yet been developed to economically optimal levels (Bewket, 2003; Guta, 2012; Mondal et al., 2017). This is due to less attention given to improving traditional

energy production, supply and utilization; little or no attention provided to developing renewable energy; non-existence of a strong energy organization; low level of household income, and lack of capital, technology, and trained human resources (Wolde-Ghiorgis, 2002). As a result, Ethiopia is the number one country suffering from domestic energy scarcity (Mulu, 2016), which has, in turn, negatively affected the environment, the education and health sectors, agriculture and overall human well-being (Marie et al., 2021).

Ethiopia lags behind other SSA countries in modern energy consumption (Mengistu et al., 2016). For instance, in 2017, modern energy, like electricity, shared approximately 13% of total energy consumption (Tiruye et al., 2021). About 95% of electricity comes from hydropower (NBE, 2020). Similarly, per-capita electricity consumption was around 93 kWh per year, which was significantly lower than the average energy consumption in SSA (521 kWh/capita/year) (MoWE, 2012). In addition, according to the Multidimensional Energy Poverty Index report, Ethiopia scored 0.9, indicating severe energy poverty (Nussbaumer et al., 2012). Efficient use of energy through improved cookstoves is very low. Therefore, most biomass fuel is used in the traditional three-stone stove (Tucho et al., 2014), with a low conversion efficiency of about 12% (Kooser, 2014; Mengistu et al., 2016).

Despite the country's progressive energy policy focus on renewables, the ubiquity of biomass fuel use remains a pervasive challenge (Guta, 2014b). Ethiopians living in off-grid areas face a severe shortage of modern and clean energy resulting in heavy dependence on traditional energy sources to satisfy household energy needs (Guta, 2020). About 87% of the population of Ethiopia remains dependent on biomass for cooking (Tiruye et al., 2021). The household sector is a major energy-consuming sector, accounting for about 88% (Benti et al., 2021). Among the various biomass fuels, energy from fuelwood is essential for sustaining livelihoods (Guta, 2014b). People access fuelwood by cutting down trees in forests, which has resulted in a significant depletion of Ethiopia’s forests (Guta, 2020). Fuelwood alone provides about 80% of the primary energy supply for households (Admasu et al., 2013). Its current use, though, is associated with burning in inefficient cookstoves (Kooser, 2014), possibly leading to a scarcity of fuelwood, deforestation and emission of noxious gases and products of incomplete combustion (Dresen et al., 2014; Tucho et al., 2014; Guta, 2020; Marie et al., 2021). In turn, this impinges on household livelihoods in a variety of ways.

Fuelwood scarcity has a greater impact on the welfare of women and children because most developing countries, including Ethiopia, are traditionally responsible for fuelwood

collection (Heltberg, 2004). When deforestation makes fuelwood scarce, women and children are forced to travel long distances and invest significant time and labour (Budds et al., 2001; Dimoso, 2009; Rogers, 2014). As a result, children at prime school attendance age routinely collect fuelwood for at least as many hours as adults (Ndiritu and Nyangena, 2011). Accordingly, children are more valuable than adults in fuelwood collection activities, which may increase the value of children (Aggarwal et al., 2001; Winkler-Dworak, 2004). This situation, however, reduces children's school attendance, study time, and, ultimately, their ability to learn and progress through school (Levison et al., 2018), which has detrimental effects on future human capital development (Koissy-Kpein, 2012). However, little attention has been given to what happens to children's school attendance following the decline in fuelwood availability.

The Ethiopian Government has been pursuing two prominent measures to address the energy access problem (Gebreegziabher et al., 2018). One of the simplest and most affordable ways is by adopting improved cookstoves designed to improve energy efficiency, remove smoke from indoor living spaces, or lessen the drudgery of cooking tasks (Damte et al., 2011; Guta, 2020). However, efforts to disseminate various fuel-saving technologies have encountered a variety of challenges, resulting in a low adoption rate. Previous studies (Dresen et al., 2014; Eshetu, 2014; Gizachew & Tolera, 2018; Mamuye et al., 2018; Adane et al., 2020; Yayeh et al., 2021) have outlined several factors that influence decision-making in changing the old cooking way to new, better ones. These factors vary depending on the context, so it is imperative to investigate the determinants of low adoption of fuel-saving stoves. Although fuelwood scarcity has reached an alarming rate in the study area, field-based analyses of traditional three-stone stoves and ICSs regarding fuelwood and time consumption are not available. In order to contribute to adoption and knowledge-based uptake of ICSs with Mirt stoves, this study seeks to provide evidence-based results on the performance of ICS and traditional stoves through Kitchen Performance Test (KPT). Another measure proposed by the Government is to accelerate the transition of households away from polluting energy sources and toward clean, renewable energy alternatives (Guta, 2020).

In light of this, the Ethiopian Government has made considerable efforts in recent years to improve access to and use of modern and clean energy sources, thereby mitigating the negative socio-economic, environmental, and health consequences of heavy reliance on biomass fuels (FDRE, 2011; Guta, 2020; Marie et al., 2021). Accordingly, about 45% of Ethiopia's had access to electricity (IEA, 2017). Similarly, rural electricity coverage has

increased from 2% in 2000 to 33% in 2018 (IEA, IRENA, UNSD, WB, 2020), and the dissemination of fuel-efficient biomass cooking stoves has grown (>10%) in recent years (MEFCC, 2018). Despite recent developments in modern and clean energy in Ethiopia and the ANRS, substantial knowledge gaps remain regarding household energy choice behaviour and factors impeding the transition. To date, little is known, and there are few scientific analyses on forest cover change and household energy utilization patterns, what factors affect household energy transition, the determinants of adopting fuel-efficient cookstoves, and the link between deforestation and children's school participation.

As indicated in various studies, household energy choices, i.e., the number of energy resources chosen by households for different use, are complex (Nikus & Wayessa, 2021). In addition, various interrelated economic and non-economic factors influence household cooking fuel choice behaviour in Ethiopia (Abebaw, 2007; Getie and Degefa, 2019; Nikus & Wayessa, 2021; Wassie et al., 2021). Previous studies (Mekonnen & Köhlin, 2008; Gebreegziabher et al., 2012; Guta, 2012; Alem et al., 2016) mainly focused on analyzing the determinants of household cooking fuel choice of a single fuel type rather than estimating the probability of choosing multiple fuel types simultaneously. However, households use multiple fuels for domestic chores to provide users with energy security. In addition, for many households, switching from traditional biomass to modern and clean energy sources may not be feasible in the short term because of the high costs coupled with the high poverty level (Guta, 2014b; Scheurlen, 2015). Thus, this study is aimed to investigate forest cover change and its implication on household energy utilization patterns and educational attainment of children in the Semien Mountains and adjacent districts, ANRS, Northwestern Ethiopia.

1.3. Objectives

The overall objective of this study was to examine forest cover changes and household energy utilization patterns in the Semien Mountains and adjacent districts in Northwestern Ethiopia.

Specifically, the study intended to address the following objectives:

- Examine the trends of forest cover changes and its drivers in the Semien Mountains National Park and adjacent districts;
- Identify and analyze the determinants of households' energy choice for domestic chores in the study area;

- ❖ Examine the performance of improved cooking stoves for fuel and time-saving and identify factors affecting the adoption of these stoves in the study area; and
- ❖ Investigate the link between fuelwood collection and children's school attendance in the study area.

1.4. Research Questions

In light of the aforementioned study objectives, this study attempted to answer the following key research questions:

- ❖ How have the forest resources of the Semien Mountains changed over time?
- ❖ What are the drivers of forest cover changes?
- ❖ How do economic and non-economic factors determine household energy choice behaviour?
- ❖ Are there significant variations in fuel and time-saving performance between *Mirt*-improved biomass cooking stoves and traditional three-stone stoves?
- ❖ How do social, economic, environmental and institutional factors influence household decisions on adopting *Mirt*-improved biomass cooking stoves?
- ❖ To what extent do fuelwood collection tasks hinder children's school attendance?

1.5. Significance of the Study

In general, research is carried out for two reasons. The first and most fundamental reason for conducting a study is to solve societal and environmental problems, improve policy and practices, and bring new practices. Most problem-driven research aims to find a solution and improve practices. Thus, their significance is determined by whether they have brought the necessary improvements. The second reason is to generate new knowledge. Since this study focuses on the link between forests, household energy utilization patterns and children's school attainment, the study contributes to knowledge generation in the field of environment, energy and education. Thus, detecting forest cover change and its drivers helps generate data that can be used to design and propose sustainable forest management intervention strategies that may assist environmental conservationists and local communities in addressing the challenges.

Moreover, millions of people in the study area and adjacent districts rely on forests found in the Semien Mountains for fuel to meet their domestic energy needs. Energy provision is inseparably linked to poverty reduction, climate change mitigation, education, food security

and public health. Likewise, household energy use patterns are linked to environmental issues such as deforestation, soil erosion, climate change, and biodiversity loss. Hence, analyzing household energy utilization patterns and identifying factors that influence choice and transition is vital. Accordingly, the findings will serve as input for policymakers and planners to develop effective policies, strategies and development programs to alleviate energy-related problems and improve household living conditions by ensuring reliable, affordable and efficient energy sources. Besides, the study will contribute to developing efficient and modern energy services, curbing environmental problems and improving livelihoods of households.

Understanding how forest cover change affects children's school attainment will provide a framework within which the issues can be examined holistically from a policy standpoint. A lack of studies demonstrating these interlinkages at the local level has been cited as one of the major issues impeding policymakers' efforts to implement sustainable efforts. Consequently, the findings of this study provide policymakers, researchers, academicians and other stakeholders in the region and country with useful empirical information for determining how to implement integrated development efforts in the area of environment, energy and education.

1.6. Scope of the Study

The discourses between environment and development are multifaceted. In recent years, the environmental discourse has increasingly gained significance in formulating development theories, models, and policies, especially under sustainable development. In the past, the mainstream theories and development models hardly addressed critical environmental and ecological issues. More recently, however, a worldwide consensus has emerged that environmental and ecological concerns represent one of the most critical factors related to socioeconomic development. The environmental discourse has gained increasing attention in almost all international forums on development, and the environment-development relationship is being seriously taken into account in practical policies and theoretical debates. However, some of the most articulate advocates of this environment-development nexus have been the proponents of a more contemporary model of development called sustainable development. Despite recognising environment-development linkages by sustainable development advocates, it tends to overlook certain crucial environmental factors. In this regard, this study was limited to the Semien Mountains and adjacent districts in the ANRS,

Northwestern Ethiopia. The study is delimited to analyze forest cover change and its implications for household energy utilization patterns and children's school attainment. Although the study is delimited to the Semien Mountains and adjacent districts, the findings can be valuable to similar agroecological areas in the region specified and even beyond. The unit of analysis is limited to households residing in and around the Semien Mountains. Satellite data from 1984 to 2020 were used to map and detect forest cover changes in the Semien Mountains and adjacent districts.

1.7. Limitation of the Study

The study is limited to one-time cross-sectional data collected from sampled households. Consequently, over time trends of important variables and their dynamic linkage is not addressed, although efforts were made to draw inferences about the long-term behaviour of some variables. Besides, conducting stove efficiency tests during different seasons helps obtain more representative data and produce more precise results. However, in this study, stove efficiency assessment was performed only once because of the costly nature of the experiment. Moreover, the KPT experiment did not include all the study kebeles because of financial constraints and anticipated difficulty managing the tests. Furthermore, the study used the energy ladder and fuel stacking model to analyze household energy choice behaviour. However, there are other theories that this study did not consider. Despite these limitations, the study makes a substantial addition to the existing knowledge on environment and development.

1.8. Theoretical Framework

This study is framed through different theories, approaches and explanations. The transition from traditional biomass fuels to modern, safe, sustainable and efficient energy sources has the potential to improve the lives of over 2.7 billion people who continue to rely on inefficient biomass fuels (IEA, 2017). With the difficult task of using these fuels, the economic, health, and environmental consequences are massive. The energy transition is, therefore, critical if such problems are to be addressed. The transition is frequently represented by analyzing factors influencing the household's choice and behaviour of energy utilization using two theoretical models: energy-ladder and energy-sacking. They differ in their approach to energy sources, but they both assume the existence of hierarchies in household energy services.

The first theoretical framework is the energy-ladder model, the dominant model used to study household energy choice behaviour in developing countries (Heltberg, 2005; Arowolo et al., 2018). Hosier & Dowd (1987) describe a pattern of fuel substitution as a household's economic situation changes. The underlying assumption is that households have a variety of energy supply options that can be arranged in ascending order of technological sophistication. As the demand for or supply of more sophisticated fuels grows, more users will switch from biomass to kerosene to electricity. Concerning the environment, this implies less strain on woody vegetation resources (Masera et al., 2000; Campbell et al., 2003). In a study by Heltberg (2005), the model strongly emphasizes income as a primary determinant of household fuel choice and switching. This indicates that a critical reason for the slow energy transition process in some backward areas is that the poor are highly likely to be trapped by the high prices of modern, high-quality fuels, forcing them to rely on low-quality energy sources for survival (Gosens et al., 2013).

As Heltberg (2005) hypothesized, the energy-ladder model envisions a three-stage fuel-switching process. At the outset, there is a heavy reliance on biomass fuels (fuelwood, dung and crop residues). However, these fuels are inefficient because they pollute the environment and human health. In the second stage, households abandon fuelwood in favour of transition fuels (coal, charcoal, and kerosene) in response to increased income and factors such as deforestation and urbanization. Finally, in the third stage, households can purchase improved cookstoves and switch to cleaner fuels (LPG, biogas, and electricity) due to better incomes and relative fuel prices. Moreover, there may be several reasons why households want to switch to fuel types higher up on the energy ladder, such as higher efficiency and lower indoor air pollution (IAP), but these fuel types are more expensive than lower-quality fuels (Wik et al., 2015). Masera et al. (2000) also implicitly assume that higher-up ladder fuel types carry a certain status and that households want to move up the ladder to demonstrate an increase in socioeconomic status.

Furthermore, the energy ladder concept is based on the microeconomic theory of rational choice (Kowsari & Zerriffi, 2011). It is assumed that all types of fuel (traditional and modern) are available, that there is a universal set of fuel preferences, and households will choose to move up the fuel ladder as soon as they can. As stated by Masera et al. (2000), households transition from traditional to modern energy systems at the rate and extent permitted by the following factors: household income, fuel and equipment costs, fuel availability and accessibility, reliability of modern fuel distribution, and, to a lesser extent,

relative fuel prices. As a result, testing the effect of income levels on energy choice can be beneficial.

The energy ladder model has been criticized in recent years for a variety of reasons. For instance, Jebaraj & Iniyan (2006) criticize the energy ladder model because it focuses too rigidly on economic processes as determinants of fuel choice, with no concern for certain social, cultural and behavioural processes as determinants of energy choice. According to this model, fuelwood is an inferior economic good, often associated with necessity rather than choice. Further, as Leach (1992) pointed out, fuelwood can be viewed as the fuel of the poor. However, Van der Horst & Hovorka (2008) illustrate that in Botswana, fuelwood is not restricted to low-income groups; all income groups widely use it due to consumer preferences and lifestyle considerations rather than income restrictions.

Another criticism of the energy ladder model is that fuel transition is not linear in many developing countries. Heltberg (2004) studied fuel-switching in 8 developing countries and found that adopting a new cooking fuel does not always displace traditional fuel. He draws on evidence that multiple fuel use is widespread in the studied regions. Similar findings have been reported in other developing countries (Ouedraogo, 2006; Van der Horst & Hovorka, 2008; Bremner et al., 2010; Akpalu et al., 2011; Kowsari & Zerriffi, 2011).

Because of these criticisms, many empirical studies on household energy consumption have revealed that fuel switching is not unidirectional, and people may return to traditional fuels after switching to modern energy carriers (Kowsari & Zerriffi, 2011). Instead of simply switching between fuels, households choose a mix of fuels and conversion technologies based on their budget, preferences, and needs (Davis, 1998; Masera et al., 2000). Hence, scholars developed an alternative theoretical model called the fuel-stacking (multiple fuels) model.

The fuel-stacking model asserts that the energy transition does not occur as a series of simple, discrete steps; instead, multiple fuel use is more common (Leach, 1992; Masera et al., 2000; Heltberg, 2004). Energy demand is driven by the services energy provides. At a subsistence level, households rely on biomass fuels for cooking and heating, which meet most of their energy needs. However, as income grows, the household can afford to purchase various appliances, each requiring a different energy source. This leads to more diversified energy demand (Kowsari & Zerriffi, 2011).

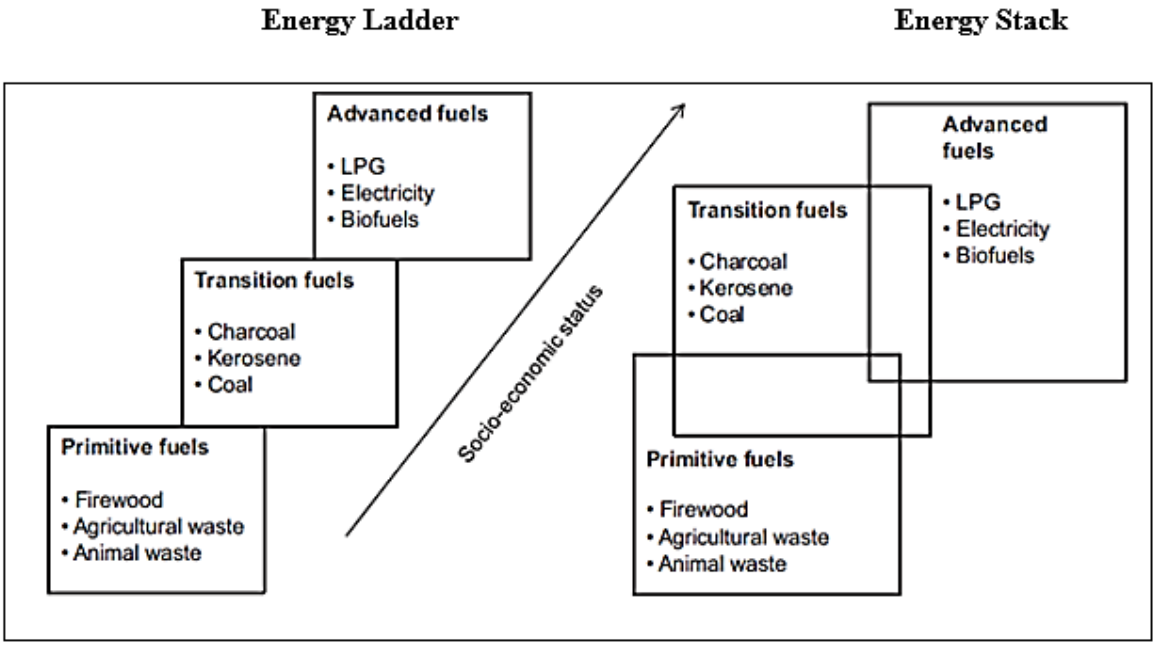

Figure 1: The Energy Model
Source: Schlag & Zuzarte (2008)

According to the fuel-stacking model, households can use both traditional and modern fuels simultaneously (Van Der Kroon et al., 2013). At various points along the energy ladder, households consume a portfolio of fuel options (Kowsari & Zerriffi, 2011). However, as Masera et al. (2000) demonstrated, households do not switch fuel but rather follow a fuel-stacking strategy in which new cooking technologies and fuels are added while even the most traditional systems are rarely abandoned. In addition, the fuel-stacking model is heavily reliant on the universal hierarchical order of different fuel choices and services assumed in the energy ladder model, and household energy choices may shift towards high-quality energy as their socioeconomic values improve (Takama et al., 2012).

The fuel-stacking model recommends that households adopt a portfolio of energy systems and consider various factors affecting the household's energy portfolio (Kowsari & Zerriffi (2011). Some of the causes of fuel-stacking include decreasing vulnerability to modern energy price fluctuations by diversifying energy use, such as using electricity for lighting and fuelwood for cooking (Leach, 1992; Thom, 2000), the inapplicability of alternative energy systems to cooking methods and preferences (Masera et al., 2000), and the high costs associated with using modern energy sources (Davis, 1998).

Although income plays a significant role in fuel choice for many, there are several factors other than income influencing household fuel choice and use. Masera et al. (2000), for instance, show that household energy choice depends on household decisions based on a

complex interaction between demographic, economic, social, cultural and environmental factors. Kowsari & Zerriffi (2011) also suggest that household fuel choice determinants are classified into endogenous (household characteristics) and exogenous (external conditions) factors.

According to Kowsari & Zerriffi (2011), endogenous factors are those that pertain to household characteristics: economic characteristics (income, expenditure, and landholding), non-economic characteristics (household size, gender, age, household composition, education, labour, and information), and behavioural and cultural characteristics (preferences, e.g., food taste, practices, lifestyle, social status, and ethnicity). In contrast, exogenous factors are external conditions that influence household decisions about their energy system by affecting the choices available to households and the incentives to choose one energy technology or fuel over another. Exogenous factors consist of the physical environment (geographic location, climatic conditions), policies (energy policy, subsidies, market, and trade policies), energy supply factors (affordability, availability, and reliability of energy supplies), and energy device characteristics (conversion efficiency, cost, and payment methods, the complexity of options) (Kowsari & Zerriffi, 2011). Thus, it is important to get an overview of these two prominent models to understand household energy utilization patterns and decision behaviour fully.

1.9. Conceptual Framework

A conceptual framework (Figure 2) was developed to guide the study and answer research questions based on theoretical insights from the literature. The framework identified certain links between changes in forest cover (deforestation and forest degradation) and patterns of household energy utilization, and children's school attendance. Forests have always been vital to Ethiopian livelihoods and the economy (Hishe et al., 2015; Danyo et al., 2017; Solomon et al., 2018). Besides, forest is the primary source of biomass energy and means of income for small holder households (Damte & Koch, 2011; FDRE, 2011; Admasu et al., 2013; Guta, 2020). The forest cover in Ethiopia has been declining for the last century (Assefa & Bork, 2014; Deribew & Dalacho, 2019; Negassa et al., 2020; Young et al., 2020). The drivers are socio-economic and political activities (Dessie, 2007). Population pressure (Asmamaw et al., 2011; Belayneh et al., 2018), agricultural expansion (Mezgebu & Workineh, 2017; Worku et al., 2016), and demand for domestic energy use (Damte & Koch, 2011; Guta, 2014b) are also contributed to forest degradation in Ethiopia. In addition, the

use of inefficient three-stone stoves by most households has led to deforestation and forest degradation (Negash et al., 2021).

Fuelwood is only regarded as renewable energy if used sustainably, whereby new trees are planted to replace the ones that are used (Negash & Kelboro, 2014). Fuelwood forms part of the energy mix in most rural and urban households, but in time, households will run out of fuelwood due to trees being harvested in an unsustainable manner (Asres, 2012). The excessive and continual harvesting of fuelwood has contributed significantly to deforestation, as many trees are cut down in collecting fuelwood, resulting in fuelwood scarcity (Guta, 2014b). With the increasing scarcity of fuelwood, households are turning to dung and crop residues for new energy, further contributing to environmental, human health and food security problems (Gwavuya et al., 2012). Besides, households will respond to energy scarcity by changing fuel choice behaviour and expenditure on adopting improved efficiency biomass stove technology (Guta, 2014a).

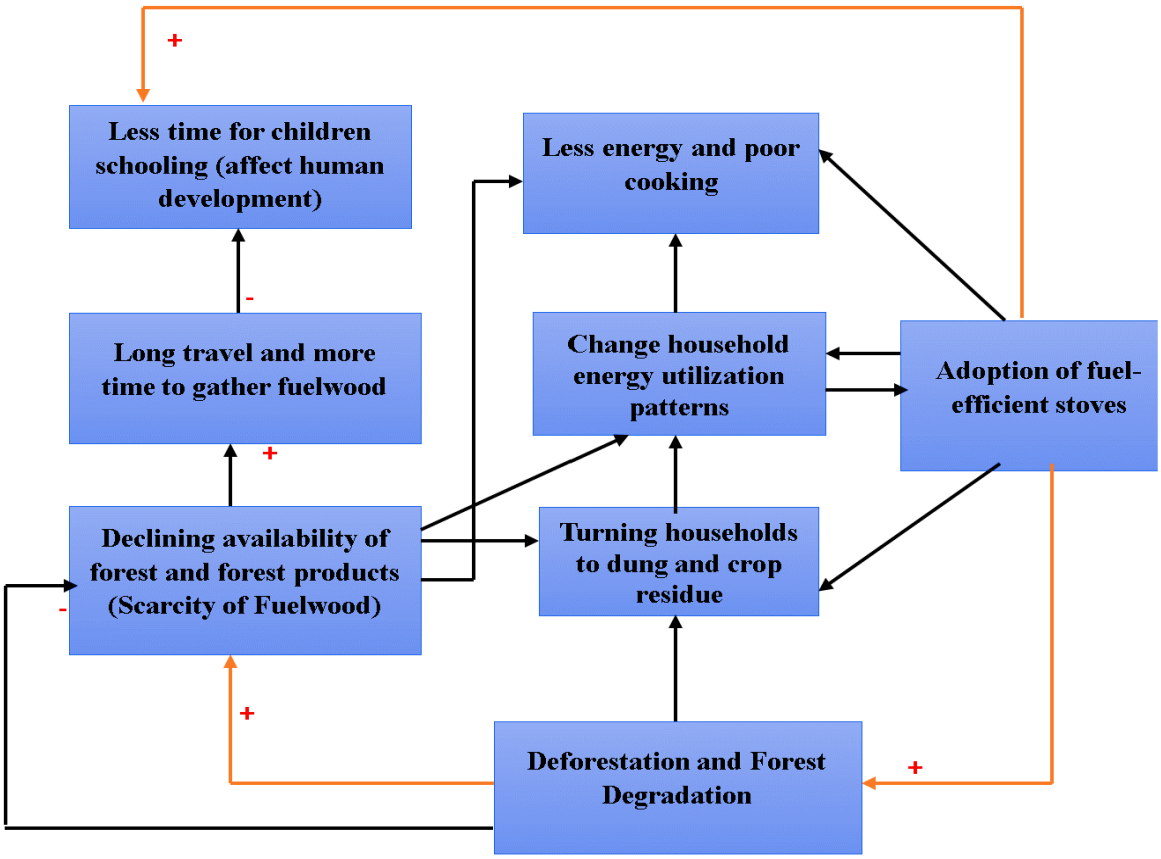

Figure 2: Conceptual Framework

Adapted and modified from (Dimoso, 2009; Gebreegziabher, 2007; Nankhuni & Findeis, 2004)

Fuelwood scarcity can have a variety of effects on households. According to Arnold et al. (2003), women and children, who are the primary collectors of biomass, bear the burden of the increase in energy collection time, which reduces the time available for other tasks such as income-generating activities and education. The framework specifically illustrates how long hours of work spent by children in fuelwood collection activities affect children's probability of attending school, using deforestation as an example of forest cover change (Dimoso, 2012). Children typically collect fuelwood in a subsistence economy like Ethiopia (Admassie, 2003). Hence, due to deforestation, children will be forced to travel farther to collect fuelwood, spending more labor and time (Ndiritu and Nyangena, 2011).

Nankhuni & Findeis (2004) discovered that Malawian children are significantly involved in resource collection work and that their likelihood of attending school decreases with additional hours allocated to natural resource collection. Ndiritu and Nyangena (2011) find that beyond a two-hour-per-day threshold, natural resource scarcity and the longer time required for resource collection have a negative impact on the school attendance of children in Kenya. A study conducted in Ethiopia by Gebru & Bezu (2013) confirms that a 50% increase in collection intensity (hours per week) reduces the likelihood of child schooling by 11%. These findings imply that as forest cover declines, the likelihood of children attending school decreases due to resource collection activities.

Therefore, intervention in energy supply and improvement in the energy efficiency of residential energy use is expected to improve livelihoods and contribute to the country's energy security (Guta, 2014a). Investment in more sustainable and efficient renewable energy use should enhance Ethiopia’s energy security and economic growth. Promoting improved cookstoves (ICSs) is an important strategy because it allows for significant fuelwood and time-savings and protects the remaining country’s forests without introducing sophisticated technologies to change cooking habits (Dresen et al., 2014; Manaye et al., 2022; Wassie & Adaramola, 2021). ICS like *Mirt* can generate about 22% to 31% in fuel saving compared to traditional three-stone stoves (Megen Power, 2008). Similarly, ICSs contribute to the reductions in time spent gathering fuelwood (Wassie & Adaramola, 2021). Generally, there are strong linkages among forest cover change, household energy utilization patterns, children’s school attendance and the adoption of fuel-efficient biomass cooking stoves in the highlands of Ethiopia.

1.10. Methodology

1.10.1. Description of the Study Area

The study was conducted in the Semien Mountains and adjacent districts of North Gondar Zone, Amhara National Regional State, Northwest Ethiopia. The Semien Mountains are located at latitude 13°29'21" to 13°29'40" N and longitude 37°51'36" to 38°34'33" E (Figure 3). It lies within five *woredas* (*districts*), including Adiarkay, Debark, Janamora, Beyeda, and Telemet, covering an area of 241,093 hectares (Debebe et al., 2023). The altitude of the SMNP ranges between 1,276 and 4,543 m with unique physiographic features: topographical ruggedness with steep escarpments, rolling hills in the highlands, and flat terraces dissected by rivers in the lowlands (EWCA, 2015). Several peaks rise from the Semein Mountains, including Ras Dejen (4,543 m), the highest peak in Ethiopia and the fourth highest in Africa (Debonnet et al., 2006). The total population was estimated to be 678,068 in 2016 (CSA, 2013b), with an average household size of 6.01 (AWF, 2019). Demographic trends since the 1950s have revealed a doubling of the population every 25 years, resulting in deforestation, farmland scarcity and shortening fallow periods on shifting cultivation land (Hurni & Ludi, 2000). In addition, most of the population (>80%) use fuelwood as their primary energy source for cooking, contributing to deforestation and forest degradation (ANRS, 2007). Altitudinal variations in the Semien Mountains have given rise to a number of rare and endemic animal and plant species (Debonnet, 2006). The study area is located in one of the wettest and coldest regions of the country, with a mean annual rainfall of between 1,350 and 1,550 mm falling in a single rainy season, whereby the highest amount of precipitation is between June and September (Hurni & Ludi, 2000). Mean daily temperatures range from a minimum of -2.5°C to 4°C to a maximum of 11°C to 18°C (Asrat et al., 2012).

The SMNP was inscribed in 1978 as one of Ethiopia's four UNESCO World Heritage Sites (Asrat et al., 2012). They are important for biodiversity conservation since it is a habitat for several endangered endemic species, including the iconic and severely endangered Walia ibex (*Capra walie*) and Ethiopian wolf (*Canis simensis*) (Debonnet, 2006). However, because of the decline of Walia ibex owing to deforestation, human settlement and cultivation, grazing, and infrastructure development, the SMNP was designated as a World Heritage Site in Danger in 1996 (Jacob et al., 2017). The area is drained and divided into different landscape features by tributaries of the Tekeze River, such as the Ansiya, Jinbar, Belegez, and Mesheha (Yohannes et al., 2020). The dominant vegetation type in the study

area comprises the Afro-montane Erica forest (*Erica arborea*), hypericum woodland, ericaceous heath-land and the Afro-montane grassland (Asrat et al., 2012; Wondie et al., 2011). Approximately 84% of the population is rural, living primarily on subsistence agriculture (AWF, 2019).

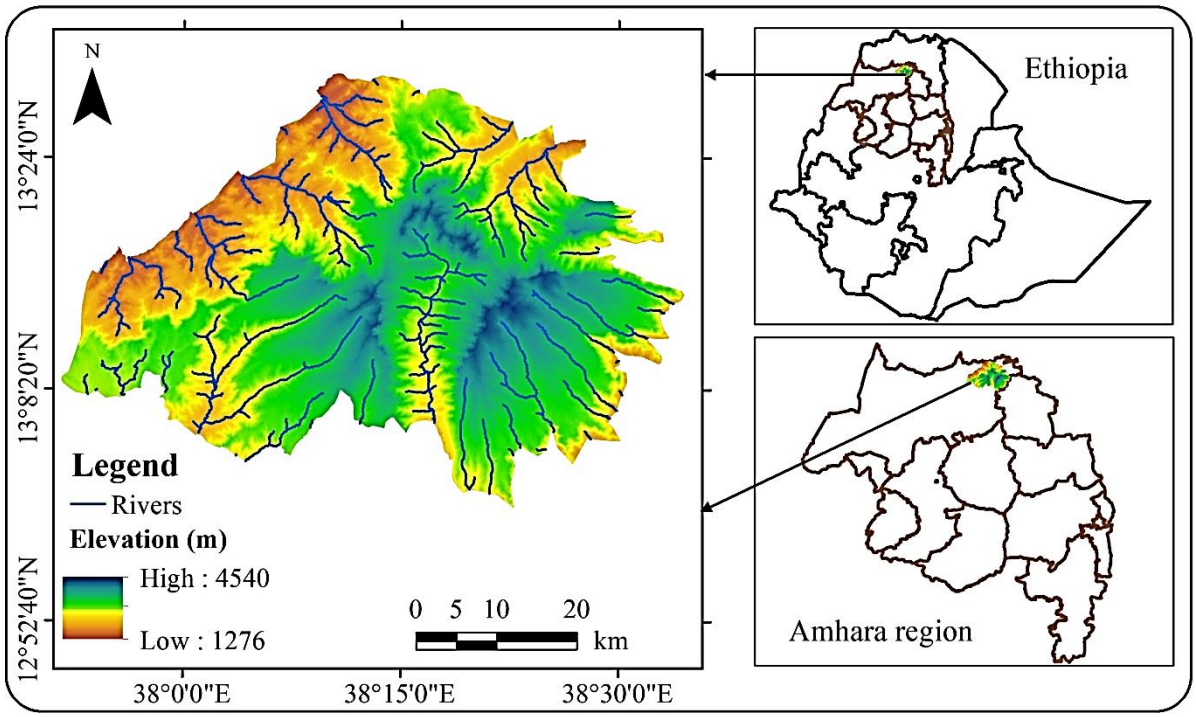

Figure 3: Map of the study area.

1.10.2. Research Design

Research design is a plan to conduct research involving the intersection of philosophy, inquiry strategies and specific methods (Creswell, 2009). As Creswell (2012) noted, research designs are types of inquiry within qualitative, quantitative, and mixed methods approaches that provide specific direction for procedures in research design. A study tends to be more quantitative than qualitative methods or vice versa. The Mixed methods approach resides in the middle of this continuum because it incorporates elements of both qualitative and quantitative methods design (Creswell, 2009).

This study used a mixed research approach, which commonly uses quantitative and qualitative skills to achieve the research objectives and answer the basic research questions raised in the study. As Creswell (2009) argued, quantitative and qualitative methods address different but complementary aspects; hence, it is commendable to use them combined. Thus, this study mostly relied on quantitative data, complemented with some qualitative evidence to triangulate evidence and raise the credibility of the findings. There are different types of

mixed-methods research designs. The present study used exploratory sequential mixed methods, in which the researchers began with a qualitative research phase and explored the views of participants. The data are then analyzed, and the information is used to build into a second quantitative phase (Creswell, 2012, 2014).

1.10.3. Sampling Technique and Sample Size

This study employed both probabilistic and non-probabilistic sampling techniques. Remote Sensing and GIS techniques were used to collect biophysical data from the entire Semien Mountains and adjacent districts, while a household survey was employed to collect socio-economic data. A multi-stage sampling technique involving both purposive and random sampling was used in this study. In the first stage, the Semien Mountains and adjacent districts were selected purposively based on the information obtained from a discussion with the zonal administrator and a panel discussion with experts and stakeholders. This is because it is one of the most environmentally degraded areas of the Amhara region, suggesting that a slight change in forest resources can have far-reaching consequences for the livelihoods of local communities relying on forests and associated forest products. In the second stage, two districts were selected based on social, economic and environmental variation purposively. In the third stage, from the selected districts, six representative kebeles (four from Debark and two from Adi-Arkay district) were selected randomly for the household survey based on distance from the Semien Mountains. Finally, representative households from the respective kebeles were selected randomly. Before selecting sample households, the list of all eligible households found in the selected Kebeles was identified, listed, revised and studied using a house-to-house survey.

Determining an appropriate sample size is crucial in any research as too small samples may hardly represent the population and lead to erroneous findings and recommendations. Hence, the overall sample size for this study was determined by using the sample size determination equation that takes into account the desired confidence level (95%), error margin (5%), and non-response rate (10%), where the sampling frame is known (i.e., 14,455 households). Accordingly, the required sample size was determined using the following equation adapted from Kothari (2004).

$$n = \frac{Z^2 * p * q * N}{e^2\,(N-1) + Z^2 * p * q}$$

where n = the required sample size; z = the upper points α/2 of standard normal distribution at 95% confidence level, which is equal to 1.96; e = the precision desired or margin of errors 5% (0.05); p = the proportion of households (which is taken as 0.5 or 50%) – the most conservative case that "n" will be the maximum and the sample yield at least the desired precision; q = 1-p; N = the total number of household heads in the selected kebeles equal to 14,455.

Table 1: Sample distribution of the surveyed households.

Districts	**Kebele**	**Total HH**	**Sample HH**
Debark	Debir	5,209	151
	Dib-Bahir	1,212	35
	Adisge-Miligebsa	1,872	54
	Adebabay Tsion	3,218	94
Adi-Arkay	Zarima	991	29
	Anguana-Kerneja	1,953	57
Total		14,455	420

The equation provided a sample size of 374 households, and it was conveniently made 420 to compensate for some non-responses and/or incomplete information. Eventually, the selected households were allocated to each kebele using probability proportional to size in each selected kebele to ensure equal representation of households.

1.10.4. Data Sources and Methods of Data Collection

The data input for this study was gathered from both primary and secondary sources to obtain quantitative and qualitative data. Spatial data like Landsat images were collected from the United States Geological Survey (USGS). Socio-economic data were collected through semi-structured questionnaires, while qualitative data was acquired through key informant interviews (KIIs) and field observations (transect walk). The details of each data collection method are described under the specific chapters in which they are employed.

1.10.5. Stove Performance Test

A preliminary survey was undertaken to identify the types of stoves and biomass fuels used, frequency of *injera* baking, family size, and the person responsible for cooking in the households. Most households in the Semien Mountains and adjacent districts were using traditional three-stone stoves for domestic use, with a small proportion of them using *Mirt-*

improved biomass cooking stoves. In this study, the Kitchen Performance Test (KPT) was selected over Water Boiling Test (WBT) and Controlled Cooking Test (CCT). The KPT was used by applying the protocol set out by Bailis (2007). The KPT is the primary field-based method to demonstrate the effect of stove interventions on household fuel usage. This type of testing, when conducted carefully, is the best way to understand the stove's impact on fuel and time saving as well as the general household characteristics and behaviours because it occurs in the kitchens of stove users. However, testing stoves through this method is the most difficult as it disrupts the daily routines of individuals. The details of the KPT procedures are stated in chapter four.

1.10.6. Secondary Methods of Data Collection

Secondary data sources, which were relevant to the subject, were also collected from both published: scientific papers, journal articles, books and reports, as well as unpublished documents: manuscripts, workshops/conferences and symposium publications. Besides, relevant forest and land use data, energy, education, and population-related data were consulted from federal, regional, zonal, districts and kebele level offices. The details are stated in each chapter.

1.10.7. Data Quality Control and Management

Different mechanisms were used to ensure the quality of the data. First, the questionnaire was translated into the local language (Amharic). A pre-test was carried out to improve the clarity of questions, ordering, and nature. Supervisors helped the enumerators with difficult situations in the field and ensured they were doing their work. Supervisors reviewed each questionnaire after the interview, identifying inconsistencies and skipped questions. The researcher reviewed the questionnaire at the end of each day's interview. Moreover, the collected data were entered into computer software immediately after reviewing the questionnaire. Then, data cleaning and checking for errors of the inconsistency of responses were undertaken. After completing the data entry, the researcher looked at the frequency distribution of variables to re-check for missing values, outliers, and other data errors. During data entry, when errors originate, it is validated against the questionnaires and corrections are made before analyses. Finally, data analyses were performed using both quantitative and qualitative methods.

1.10.8. Data Processing and Analysis

The collected data were edited, coded, and classified before entering into the Statistical Package for Social Scientists (SPSS v.2020) software. The data was then cleaned and checked for errors and inconsistencies before being exported to STATA 14 for analysis. Finally, in line with the study's objective, descriptive statistics and regression analysis, satellite image analysis using remote sensing and GIS techniques and narratives were used to analyze the quantitative and qualitative data (Table 2). The details of each method of data analysis are provided in the respective chapters.

1.10.9. Structure of the Dissertation

This dissertation is organized into six chapters. The first chapter provides an overview of the research, including the research context, problem statement, main research questions and objectives, theoretical and conceptual framework, and research design. From Chapter Two to Chapter Five, the main findings of the study are presented. They are independent chapters with an introduction, materials and methods, empirical results and discussions, and a conclusion section. Chapter two analyzes forest cover change and its drivers in biodiversity hotspot areas of the Semien Mountains National Park of Northwestern Ethiopia. The third chapter examines household energy utilization patterns and the factors influencing household energy choice for domestic chores. The fourth chapter discusses the adoption and performance of improved biomass cooking stoves and the implications for energy savings. The fifth chapter discusses the link between fuelwood collection and children's school attendance. Finally, chapter six synthesis the main results of the previous chapters and describes scientific insights and implications for energy utilization challenges and issues for future research.

Table 2: Tabular summary of the Methods applied in the dissertation.

Objectives	**Study Design**	**Data Sources**	**Sample Size used**	**Data Collection Techniques**	**Method of Data Analysis**
Examine the trends of forest cover changes and their drivers in the Semien Mountains National Park and adjacent districts.	Cross-sectional study design Exploratory sequential mixed methods	Primary and Secondary data from spatial and non-spatial data	420 households 15 KIIs	Spatial data: four sets of Landsat images Non-spatial datasets: socio-economic data (Structured Questionnaire survey, KIIs & field observation)	Landsat imageries were analyzed using ERDAS IMAGINE 14, ArcGIS 10.7 & QGIS 2.41. Socio-economic data were analyzed using descriptive Statistics: Mean, figures & percentage.
Identify and analyze the determinants of households' energy choices for domestic chores.	Cross-sectional study design Exploratory sequential mixed methods	Primary and secondary data	420 households 10 KII	Socio-economic data (Structured Questionnaire survey, KIIs & field observation)	Descriptive statistics and econometric model: Multivariate probit model
Examine the performance of improved cooking stoves for fuel and time-saving and identify factors affecting the adoption of these stoves.	Kitchen Performance Test and Cross-sectional study design Exploratory sequential mixed methods	Households residing in the Semien Mountains and adjacent districts	15 *Mirt* and 20 three-stone stove users for KPT and 420 households 10 KIIs	KPT test to estimate fuel & time-saving performance of *Mirt* stove. Socio-economic data (Structured Questionnaire survey, KIIs & field observation)	Descriptive statistics: mean, percentage, figures. Bivariate statistics: chi-square and t-test Econometric model: Binary logistic regression model
Investigate the link between fuelwood collection and children's school attendance.	Cross-sectional study design Exploratory sequential mixed methods	Households residing in the Semien Mountains and adjacent districts	679 school-aged children collected from 420 households 10 KIIs	Structured Questionnaire survey and KIIs	Descriptive statistics: mean, percentage, figures Bivariate probit model and 2SCML regression model

CHAPTER TWO: ANALYSIS OF FOREST COVER CHANGE AND ITS DRIVERS IN BIODIVERSITY HOTSPOT AREAS OF THE SEMIEN MOUNTAINS NATIONAL PARK, NORTHWEST ETHIOPIA

ABSTRACT

Forests provide multiple ecosystem services ranging from local livelihoods and socio-economic benefits to global ecological services. Despite these benefits, human activities have put immense strain on forest resources, resulting in forest degradation, impoverishment of the environment, and loss of livelihoods. Hence, quantifying forest cover change and identifying its drivers are essential for developing sustainable forest management strategies to restore forest resources and ecosystem services. This study examined the trends of forest cover changes and its drivers in and around the Semien Mountains National Park, Northwest Ethiopia, from 1984 to 2020. Data from Landsat satellite images of 1984, 1996, 2008, and 2020 were used for forest cover mapping and quantifying the changes using remote sensing techniques. A household survey and key informant interviews were also used to identify the drivers of forest cover change. Results showed an overall decline in forest cover and grasslands, while cultivated lands, bare lands, and built-up areas have registered gains in the study area. The percentage area under forests declined by about 31% (33,084 ha) over the past 36 years. This loss translates to an annual average forest loss of about 1.02% (919 ha). Conversely, cultivated land, bare land, and built-up areas have experienced an increase of about 159% (33,387 ha), 220% (10,121 ha), and 366% (6356 ha), respectively, over the last 36 years. Analysis of the 36-year change detection matrix revealed that about 62% of the study area experienced a transition, of which 21% and 41% were attributable to net and swap changes, respectively. The observed reduction in forest cover was driven by agricultural expansion, population growth, growing demand for fuelwood, livestock pressure, and forest fires. Such drastic changes in forest cover have a detrimental impact on the community's well-being, biodiversity, climate, and the availability of forest ecosystem services. Thus, the study recommends concerted efforts by stakeholders to develop participatory forest management and public awareness that consider the co-existence of nature conservation and sustainable livelihoods.

Keywords: Deforestation; Forest; Gain; Gain-to-persistent; Loss; Loss-to-persistent; Net change; Persistence; Swap change

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2.1. Introduction

Forests, covering about 30.8% of the global land area (FAO, 2020), are home to most of the terrestrial biodiversity on Earth and provide multiple ecosystem goods and services (Deka et al., 2018; Duguma et al., 2019). It sustains the major life support system on earth and is essential for the development of the social and economic sectors of many countries (Jebiwott et al., 2020). Moreover, forests are vital sources and sinks of carbon (Köhl et al., 2015), protecting soil and water resources as well as biodiversity conservation and climate change mitigation (Miura et al., 2015), and are essential for subsistence, employment, and income sources for some 1.6 billion people globally (UN, 2017), and are a source of energy for over two billion people (Bošković et al., 2018). However, to meet their daily needs, humans have consistently deforested and fragmented large tracts of forestlands worldwide (Ken et al., 2020) and threatened the availability of forest ecosystem services (Sulieman, 2018).

Even though deforestation has reduced globally, it continues to be a primary concern in environmental discussions in tropical countries (Sulieman, 2018). Tropical forests constitute an important ecosystem in the world due to the numerous resources and ecosystem services they provide to support human life (FAO, 2020). However, they are beset with the problem of human disturbance, reducing their ability to perform their ecosystem function (UN, 2017). A recent report by FAO and UNEP (2020) revealed that between 1990 and 2020, the global forest area declined by 4.4%, representing a net loss of 178 million ha. About 6 million ha of primary forest is lost each year globally in response to agriculture, poverty, urban expansion, infrastructure development, fuelwood extraction, forest fires, and other human activities (FAO, 2015; Addo-Fordjour & Ankomah, 2017; Ahammad et al., 2019; Ngwira & Watanabe, 2019). Hence, forest loss can potentially interrupt important ecological services provided by forests and lead to overall impoverishment of the environment and loss of livelihoods (Käyhkö et al., 2011; Gebrehiwot et al., 2014; Ahammad et al., 2019). This phenomenon is more pronounced in developing countries, where most of the world's tropical forests exist.

The rates of forest cover changes in different countries or regions are not uniform but vary over time and space (Lambin et al., 2003). In some places, forest cover is slightly increased, while in others, it is declining. For instance, the highest percentage of annual forest loss was reported in developing countries, particularly in Africa (at 3.94 million ha year^{-1}), followed by South America (at 2.6 million ha year^{-1}), while in a few countries in Asia, Oceania, and Europe, a reverse trend of increasing forest cover has been reported (FAO, 2020). The

difference in the trends in forest cover change among regions partly reflects differences in forest management practices, policies, and weak enforcement (Addo-Fordjour & Ankomah, 2017) and the changes in land use demands (Rotich & Ojwang, 2021) that promote deforestation.

Like many other developing countries, forests are vital to the socioeconomic and environmental well-being of Ethiopia (Duguma et al., 2019). Securing food, fuel and livelihoods for the country's growing population is inseparably linked to the exploitation of forest resources (Baye, 2017). Despite their wide-reaching significance, forest resources in the country have been declining both in size (deforestation) and quality (degradation) (Young et al., 2020). As estimated by Pohjonen and Pukkala (1990), at the turn of the twentieth century, some 40% of Ethiopia and 90% of the highlands (> 1500 m above sea level) were forested. However, much of the forests had been cleared and reduced to 16% in the 1950s and shrank further to 2.7% in the 1990s (EFAP, 1993). The clearance and regeneration of forests occurred sporadically until the 20th century, after which deforestation became much more pronounced. Although reliable and consistent data on deforestation are scarce and contentious in Ethiopia, various sources have reported varying figures. For instance, Pohjonen and Pukkala (1990) reported that the annual rate of deforestation in Ethiopia was about 800,000 ha year^{-1} during the 1950s, 163,000 ha year^{-1} between 1986 and 1990 (Reusing, 1998), and 141,000 ha year^{-1} between 1990 and 2010 (FAO, 2010b). The difference between estimates of deforestation is attributed to much of the information having been derived from indirect sources and not from quantitative empirical studies.

The drivers of forest cover change in Ethiopia are dynamic and complex, varying in space and time depending on diversity in vegetation types, environmental history, livelihood, and topography (Assefa & Bork, 2014). However, recent studies in Ethiopia have revealed that the human factor, including population growth, uncontrolled fuelwood extraction, poverty, lack of forest and land-use policies, unstable land-tenure system, and socio-political instability, are responsible for forest cover change (Kindu et al., 2013; Gebrehiwot et al., 2014; Gebrelibanos & Assen, 2015). Additionally, recent urban expansions and infrastructure development have exerted pressure on forest cover in Ethiopia (Duguma et al., 2019). It is, therefore, impossible to generalize that forest cover changes occur on a broader scale, and the drivers influencing these changes are inherent landscapes.

Although deforestation is a common phenomenon and affects all of Ethiopia, the highlands are the most vulnerable area due to a long settlement and agricultural history (Gebrehiwot et al., 2014; Belayneh et al., 2018). Various studies have been conducted in Ethiopia to examine forest cover change using GIS and remote sensing methods (Assefa & Bork, 2014; Gebrehiwot et al., 2014; Mezgebu & Workineh, 2017; Belayneh et al., 2018; Badesso et al., 2020). These studies have documented that forest resources have declined both in space and time. Conversely, other studies have reported a slight increase in forest cover in some parts of the country (Bantider et al., 2011; Moges & Bhat, 2018). These disparate findings necessitate time and location-specific research using integrated research approaches.

The Ethiopian highlands, particularly the northwestern highlands, have experienced rapid and extensive land cover (LC) conversions, leading to loss of biodiversity, climate change, soil erosion, shortage of forest products, food insecurity and poverty (Gebrehiwot et al., 2014; Belayneh et al., 2018; Duguma et al., 2019). Hence, quantifying and monitoring land cover change over time has become an increasingly important consideration for environmental and development management interventions (Rotich & Ojwang, 2021). Different studies have been conducted to quantify land cover change in the northwestern highlands (Zewdie & Csaplovics, 2015; Wubie et al., 2016; Moges & Bhat, 2018). These studies, however, tend to emphasize the rate of change rather than the attributable causes. In addition, they mainly focused on changes in land cover, primarily observed in the lower-altitude vegetation belts. However, reliable and consistent data on forest cover change have yet to be well-documented and quantified in relatively unknown, sensitive, and biodiversity hotspot areas of high-altitude forests in the Semien Mountains National Park (SMNP). High-altitude forests, like the Semien Mountains, are vital to ecosystem stability because they store rainfall, regulate flows, reduce soil erosion, and protect against floods, landslides, and rockfall (Chaudhary et al., 2017).

The SMNP, characterized by a wealth of biodiversity and ecosystem services, is one of Ethiopia's most important biodiversity hotspot areas. It also has global and local significance. Although the SMNP is a global biodiversity hotspot area, its forest resources are constantly under increasing threat due to people's dependence on forests for energy consumption as well as forest products for livelihoods (ANRS, 2007). Even though deforestation is a common phenomenon, the gains and losses of forest cover from specific areas vary over time (Gebrehiwot et al., 2014). Few studies have been carried out to quantify the spatial and temporal aspects of LC change in the SMNP (Wondie et al., 2011; Jacob et

al., 2017). These studies, however, are partial in their spatial coverage and have not provided concrete evidence on forest cover change and its drivers using an integrated approach. The use of remote sensing (RS) and geographical information systems (GIS) in mapping and quantifying forest cover changes over time is crucial as it provides adequate information for identifying conservation hotspots to support decision-making for sustainable forest management (Kindu et al., 2013; Assefa & Bork, 2014; Rotich & Ojwang, 2021). However, it cannot provide an explanation about why and how changes occur (Fisher, 2012). As a result, integrating RS and GIS technologies with local land users' knowledge is vital to assess the trends in forest cover change and identify the drivers (Ahammad et al., 2019).

Therefore, this study aimed to (i) quantify the spatiotemporal changes in forest cover over the past 36 years and (ii) identify the drivers of forest cover change in the rapidly changing environment of the SMNP. The findings of this study will contribute valuable information for developing future conservation policies and strategies for forests in Ethiopia and other developing countries. In addition, the study will add to the existing literature on the deforestation process in Ethiopia.

2.2. Materials and Methods

2.2.1. Description of the Study Area

The SMNP is situated in North Gondar Zone, the Amhara National Regional State (ANRS), Northwest Ethiopia. It lies between latitude 13°29'21″ to 13°29'40″ N and longitude 37°51'36" to 38°34′33″ E (Figure 4). The SMNP spans five *Woredas* (D*istricts*), including Adi-Arkay, Beyeda, Debark, Janamora, and Telemt (Chernet, 2015). The altitude of the SMNP ranges between 1,276 and 4,543 m above sea level, with unique physiographic features: topographical ruggedness with steep escarpments, rolling hills in the highlands, and flat terraces dissected by rivers in the lowlands (EWCA, 2015). Several peaks rise from the Semein Mountains, including Ras Dejen (4,543 m above sea level), the highest peak in Ethiopia and the fourth highest in Africa (Debonnet, 2006). The Semien Mountains have a unimodal rainfall distribution between June and September, ranging from 1,350 to 1,600 mm, whereas a mean daily temperature of −2 and 18 °C (Asrat et al., 2012). Owing to the differences in topography and geological events, different soil types, including Andosol, Phaeozem, Vertisol, Luvisol, Regosol, and Leptosol, exist (Hurni & Ludi, 2000). Mixed subsistence farming is the principal source of employment and income for most households (ANRS, 2007). Forests, grasslands, cultivated land, and bare/degraded land are the most

common LULC (EWCA, 2015). The Semien Mountains serve as a key water tower for downstream users, forming tributaries to the Tekeze River, which supplies water to millions of people in Ethiopia, Sudan, and Egypt (Hurni & Ludi, 2000).

The SMNP was inscribed in 1978 as one of Ethiopia's four UNESCO World Heritage Sites (Asrat et al., 2012). They are important for biodiversity conservation since it is a habitat for several endangered endemic species, including the iconic and severely endangered Walia ibex (*Capra walie*) and Ethiopian wolf (*Canis simensis*) (Debonnet, 2006). However, because of the decline of Walia ibex owing to deforestation, human settlement and cultivation, grazing, and infrastructure development, the SMNP was designated as a World Heritage Site in Danger in 1996 (Jacob et al., 2017). Furthermore, the Semien Mountains are part of the Afroalpine Center of Plant Diversity and the Eastern Afromontane Biodiversity Hotspot of plant diversity, comprising over 1200 plant species and three endemics to the Semien Mountains (EWCA, 2015).

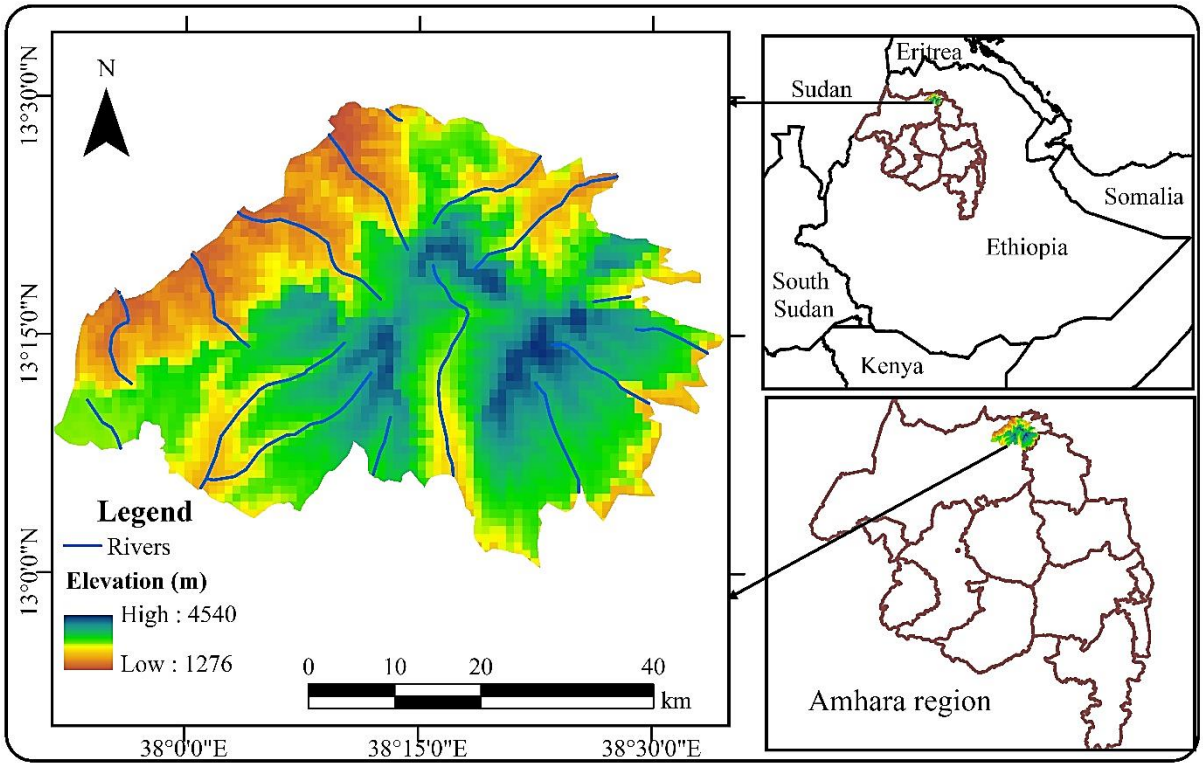


Figure 4: Location Map of the Semien Mountains and Adjacent Districts.

2.2.2. Data Type and Source

The study used both spatial and non-spatial (socio-economic) datasets from primary and secondary sources. The primary data were obtained from Landsat images, Google Earth, household surveys, key informant interviews (KII), and field observations. In contrast,

secondary data were obtained from published materials, government reports and abstracts, and policy documents.

2.2.3. Spatial Data Acquisition

Four sets of satellite imagery, such as Landsat 4–5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI), of 1984, 1996, 2008, and 2020, respectively, were acquired from the United States Geological Survey (USGS) http://glovis.usgs.gov (Table 3). Images were captured during the dry season (January) to minimize the probability of classification error due to cloud cover and seasonal vegetation change. The imagery dates were defined based on major events that affected forest cover changes. For example, we selected 1984 as a period when the country was hit by drought, so forest cover change was expected; 1996 designated a period after the overthrow of the Derge regime so that massive deforestation and cropland expansion was assumed; and 2008 as a period when forest development, conservation, and utilization policies and strategies were launched. Finally, 2020 was selected to examine the current status. The satellite images were processed using ERDAS Imagine 2015, ArcGIS 10.7, and QGIS 2.41 software.

Table 3: Characteristics of Satellite imageries used in the study.

Images	Sensor	Pixel Resolution (m)	Path	Row	Acquisition Date	Bands used
Landsat 4-5	TM	30 * 30	169	51	31/12/1984	1-5 & 7
Landsat 4-5	TM	30 * 30	169	51	24/01/1996	1-5 & 7
Landsat 7	ETM+	30 * 30	169	51	01/01/2008	1-5 &7
Landsat 8	OLI	30 * 30	169	51	10/01/2020	2-7

TM: Thematic Mapper; ETM+: Enhanced Thematic Mapper plus; OLI: Operational Land Manager

2.2.4. Ground Truth Data

Ground truth data (reference data) for land cover classification and accuracy assessment were collected using various sources. The reference data for the historical images (1984, 1996, and 2008) were collected from Google Earth images supplemented by field visits and interviews with local elders (Lossou et al., 2019). In a participatory approach, information gathered from older people is a good reference data source for validating historical LULC maps (Ewunetu et al., 2021). Therefore, old toposheets were used to initiate the discussion among members of the elderly. For the recent images (2020), ground reference data were collected from a field survey using a handheld Garmin Global Positioning System (Garmin Etrex; 10 with ± 10 m accuracy). We supplemented these with a few ground reference points

taken from Google Earth for some inaccessible areas. After considering the area of each land cover class, a stratified random sampling technique was employed to determine an optimal number of ground truth points for classification. Accordingly, 1,717 sample points were collected from the representative LULC classes for the study years. Of these ground truth points, 1,303 were used for image classification, while 414 sample points were used for the accuracy assessment of image classification for 2020 images.

2.2.5. Socio-economic Data

Socio-economic data were collected from individual farmers and foresters via questionnaires, KIIs, and field observations to examine the drivers of forest cover changes in February 2021. Six kebeles from two districts were randomly selected for the survey. The household surveys were administered to 420 households using a systematic random sampling technique. The household survey aimed to examine socioeconomic conditions, perception of forest cover change and its associated drivers, and availability and perception of forest ecosystem service changes. Interviews were also conducted with purposively selected three officers from the forestry office and two from the Semien Mountains Park office to identify the problems and the current conditions of forests in the study site. In addition, ten local people over the age of 55 years who had lived in the area for more than 30 years were interviewed to gather historical data on forest cover changes and their drivers.

2.2.6. Satellite Image Pre-Processing

The satellite images have undergone both pre-and post-processing (Figure 5). To maximize classification accuracy, input images must have minimal contamination from clouds, haze, shadow, or other disturbances (Azzari & Lobell, 2017). Since the SMNP is very rugged and mountainous, all Landsat images were topographically corrected with C-correction (Teillet et al., 1982) to reduce topographic variability in observed reflectance (Hale & Rock, 2003). The C-correction was performed by the free QGIS 2.41 program. In addition, atmospheric and radiometric corrections of all Landsat images acquired for the different years were made using a fully image-based technique developed by Chavez (1996) called the Cost model; this model derives its input parameter from the image itself. The COST model was used to convert the at-sensor spectral radiance to reflectance at the surface of the Earth. It is a Dark Object Subtraction (DOS) extension that includes a multiplicative correction for transmittance (López-serrano et al., 2016). Hence, COST incorporates all the elements of the DOS for haze removal and a procedure for estimating the effects of atmospheric gas

absorption and Rayleigh scattering (Teferi et al., 2010). This correction was performed by implementing the algorithm in ERDAS Imagine 2015.

Moreover, the Landsat 7 image dated 01 January 2008 was affected by scan line corrector (SLC) off failure due to mechanical failure. Thus, scan lines were removed to enhance the image's visual appearance using the Landsat toolbox's 'fix Landsat 7 scan line errors' of ArcGIS software (Abir & Saha, 2021). Finally, to ensure consistency between datasets throughout the classification and analysis process, all images were projected to the Universal Transverse Mercator (UTM) map Projection System, Zone 37N, and the Datum of the World Geodetic System (WGS84).

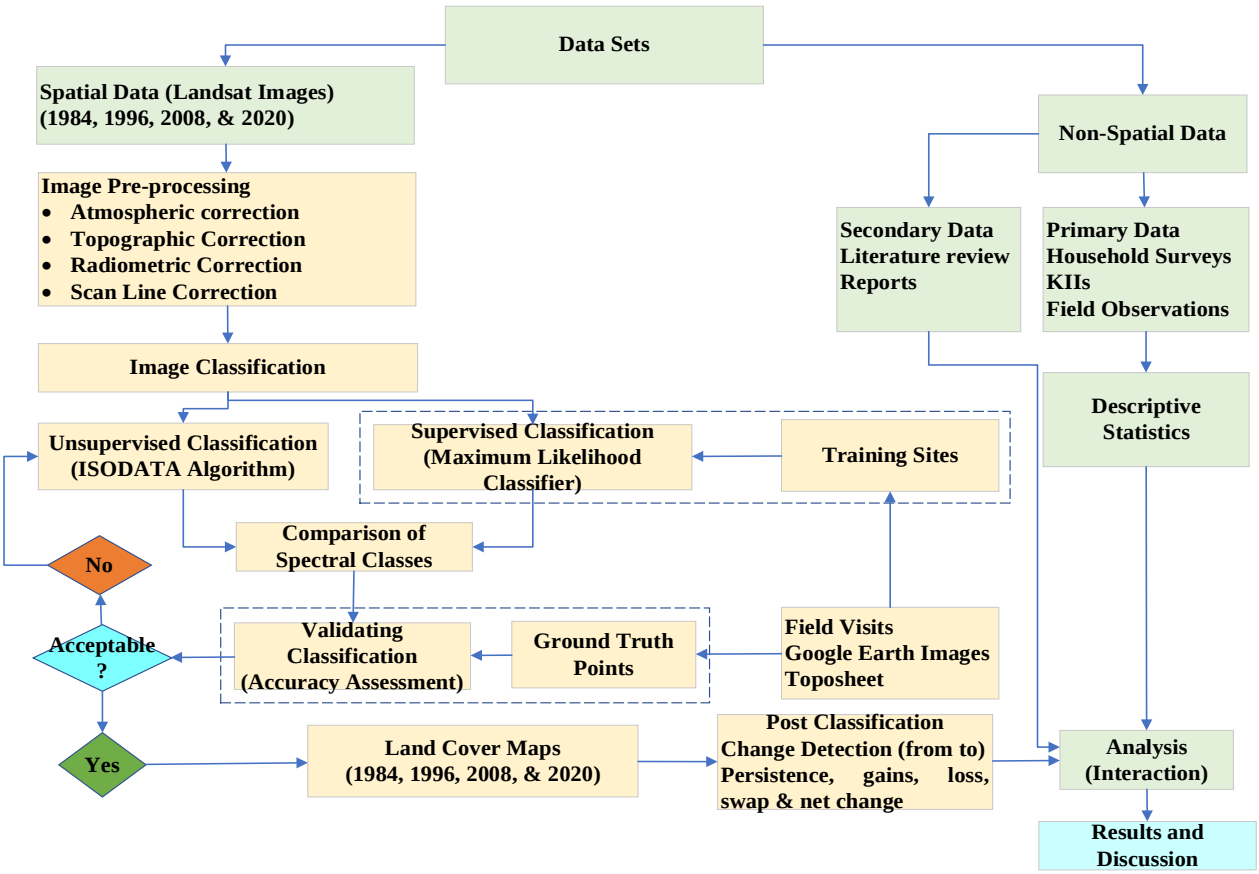


Figure 5: Flow chart showing the process undertaken during the study.

2.2.7. Image Classification

Following image pre-processing, both unsupervised and supervised image classification techniques were employed (Teferi et al., 2010). Initially, unsupervised classification was applied using the iterative self-organizing data analysis (ISODATA) algorithm to determine spectral clusters in images with ERDAS Imagine Version 15 (Teferi et al., 2010; Gashaw et al., 2017; Baral et al., 2018; Munthali et al., 2019; Abir & Saha, 2021). Then, supervised

image classification was performed after collecting training data from the existing LC classes (Ewunetu et al., 2021). From each of the predetermined LC classes, the signatures of polygons were delineated based on information gathered from field observations, elders, and Google Earth (Teferi et al., 2013; Baral et al., 2018). The pixels contained in these polygons were used to record the spectral signatures of the corresponding LC class acquired from satellite imagery (Teferi et al., 2010). A polygon of the homogenous map class was selected as a sample unit instead of a single pixel (Ewunetu et al., 2021). This was done to reduce misregistration and to increase the quality of the match of image segmentation analysis (Munthali et al., 2019). The classification was then performed using Landsat pixels that overlapped the training areas. The number of training sites varied from one LC to another depending on the ease of identification and level of variability (Ewunetu et al., 2021). Then, each pixel of the image dataset was placed in the LC class via the maximum likelihood classifier (MLC) algorithm in ERDAS Imagine 15 (Teferi et al., 2010). The MCL algorithm is the most widely adopted classification algorithm and uses a per-pixel method to account for the spectral information of LC classes (Teferi et al., 2013). A classification scheme of LC classes was developed for the study area (Table 4) based on a reconnaissance field survey, Google Earth imagery, and supplementary ancillary data (Teferi et al., 2010; Munthali et al., 2019; Ewunetu et al., 2021).

Table 4: Description of LULC types.

LULC types	**Description**	**Code**
Forest	Land spanning at least 0.5 ha, covered by dense natural forests, open woodland, moist mountain forest, plantation, and riverine forests, attaining a height of at least 2m and a canopy cover of at least 20% (MEFCC, 2016).	**F**
Grassland	A naturally patchy pattern with long and short grass and giant Lobelia is prevalent above the treeline used as a natural habitat for many species and grazing (Hurni & Ludi, 2000).	**GL**
Cultivated land	Areas under crops and fallow land. Since the rural settlements are scattered and close to cultivated lands, croplands and rural settlements were classified together (Miheretu & Yimer, 2017).	**CL**
Bare/Barren land	Areas with little or no vegetation cover consist of barren, eroded landscapes and or exposed rocks (Ewunetu et al., 2021).	**BL**
Built-up area	Areas dominated by towns, residential areas, roads, hotels, and campsites (Gashaw et al., 2017).	**BUA**

2.2.8. Post-Classification Processing

2.2.8.1. Accuracy Assessment

Classification is only complete once it achieves a satisfactory level of accuracy (Miheretu & Yimer, 2017). Before analyzing change detection, the accuracy of digitally classified images must be validated (Kindu et al., 2013). An accuracy assessment involves generating a set of points for the classified image and comparing their positions with ground truth data (Congalton & Green, 2009). These sets of points were chosen at random. For this purpose, stratified random sampling was used by allocating sample points to each LULC class. Training points that were used in classification were not used for accuracy assessment. Accordingly, 414 reference points were collected from field surveys, interviews with elders, and ancillary data: Google Earth images and NDVI maps generated by a stratified random sampling technique (Congalton & Green, 2009; Assefa & Bork, 2014) to validate the accuracy of the classified images. A confusion matrix was then used to evaluate classification accuracy (Teferi et al., 2010). An error matrix compares information from reference data to information on the classified map for some sample areas (Haque & Basak, 2017). Finally, based on Congalton and Green's (2009) formula, we calculated overall accuracy, producer's and user's accuracy, and kappa statistics.

2.2.8.2. Change Detection Analysis

A post-classification image comparison algorithm was used to determine the changes observed and the transition between different LC classes (Soffianian & Madanian, 2015). This technique compares classified maps and provides "from-to" change class information. For instance, to examine LC change, the whole study period (1984–2020) was classified into four sub-periods (1984–1996, 1996–2008, 2008–2020, and 1984–2020). The LC change transition matrix was then computed in ArcGIS 10.8 using the overlay procedure to detect, compare, and analyze change patterns and direction, as well as to quantify persistence (the diagonal element in the matrix table indicates the proportion of the landscape that did not change spatially over a period) (Baral et al., 2018), gains (the difference between the column totals and persistence) (Teferi et al., 2013), losses (the difference between row totals and persistence) (Yesuph & Dagnew, 2019), net change (absolute value) indicates the difference between gain and loss (Pontius et al., 2004), total change (the sum of net change and swap or the sum of gains and losses) (Baral et al., 2018; Yesuph & Dagnew, 2019), and swapping (denotes the concurrent gain and loss of a given land cover class) (Yesuph & Dagnew, 2019)

and is computed by subtracting net change from the total change or two times the minimum of the gain and loss (Pontius et al., 2004) of LC that occurred in the study period (Pontius et al., 2004; Braimoh, 2006).

In addition, the exposure of each LC class to a change was assessed using the loss-to-persistence ratio (L_p = loss/persistence), which assesses the vulnerability of LC classes to transition; gain-to-persistence ratio (G_p = gain/persistence), which measures the gain of a LULC to its time one size, and net change-to-persistence ratio (Np = net change/persistence) (Ouedraogo, 2010). Values of G_p and L_p greater than one imply that a given LC has a higher probability of changing to another LC class than persisting in its current condition (Braimoh, 2006). If the value of N_p were negative, the LC class would have a higher probability of losing area to other LC types than gaining from them (Adugna et al., 2017). Furthermore, to compute the annual rate of LC changes at different periods, the compound-interest-rate formula proposed by Puyravaud (2003) was used since it provides a standard method for making LC change comparisons that are insensitive to the different periods between observation dates (Teferi et al., 2013).

$$r = \left(\frac{1}{t_2 - t_1}\right) \text{x} \ln\left(\frac{A_2}{A_1}\right) \text{x } 100$$

where, r = annual rate of change, and A_1 and A_2 = area coverage of LC class at times t_1 and t_2, respectively.

2.3. Results

2.3.1. Classification Accuracy

An accuracy assessment was performed to validate image classification using a confusion (error) matrix. The diagonal values of an error matrix indicate reference data that are accurately classified, while the off-diagonal entries are misclassified references that correspond to various LC classes (Table 5). According to the classification report, the classification had an overall accuracy of 90%, with a kappa coefficient (Khat) value of 0.88 attained for the 2020 classified map. Similarly, overall classification accuracies achieved were 89.9% (with khat of 0.87) for 2008, 89.3% (with khat of 0.87), and 88.6% (with khat of 0.85). The user's and producer's accuracy in each LC class ranged from 88.8% (BL) to 91.5% (BU) and 87.4% (GL) to 93.8% (BU), respectively. Applying the methods of Congalton and Green (2009), the kappa coefficient values indicated strong agreements

between the ground truth and the classified classes. Hence, the classified maps met the minimum accuracy requirements for the subsequent change detection analysis.

Table 5: Accuracy Assessment results of 2020 image classification.

	Reference Data 2020						
Classified Data	GL	BL	CL	F	BU	Row Total	UA
GL	**83**	2	2	4	1	92	90.2
BL	4	**71**	3	0	2	80	88.8
CL	1	3	**73**	1	2	80	91.3
F	5	1	2	**72**	0	80	90.0
BU	2	2	3	0	**75**	82	91.5
Column total	95	79	83	77	80	**414**	
PA	87.4	89.9	88.0	93.5	93.8		90.3

OA: 90%; Kappa coefficient (khat) value: 87.9%

2.3.2. Status of Land Cover in and around the SMNP

Five LULC classes and four maps were identified and produced in the study landscape for the reference years 1984, 1996, 2008, and 2020 (Table 6 and Figure 6). In 1984, the SMNP and adjacent districts were dominated by forests and grasslands, covering about 45% and 44% of the landscape, respectively, while non-vegetated lands (cultivated land, bare land, and built-up areas) covered the smallest area (11%). In 1996, grassland (~42%) replaced forests as the primary LC type, while forests retained their position as the second-largest LC class, accounting for about 37% of the total area. Cultivated land, bare land, and built-up areas are all steadily growing. In 2008, grasslands (39%) occupied the largest portion of the study area, followed by forests (37%) and cultivated land (18%). The remaining portions (6%) were occupied by bare land and built-up area. Grasslands continued to be the dominant LC class (37%) in 2020, followed by forests (31%) and non-vegetated LC classes (32%) (Table 6).

Table 6: Summary of LULC change (in ha and %) from 1984-2020.

LULC	1984		1996		2008		2020	
type	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
F	108282	44.9	95384	39.6	88387	36.7	75198	31.2
GL	105477	43.7	102072	42.3	93901	38.9	88696	36.8
BL	4591	1.9	7095	2.9	9501	3.9	14712	6.1
CL	21005	8.7	32658	13.5	43261	17.9	54392	22.6
BUA	1739	0.7	3884	1.6	6043	2.5	8095	3.4
Total	241093	100.00	241093	100.00	241093	100.00	241093	100.00

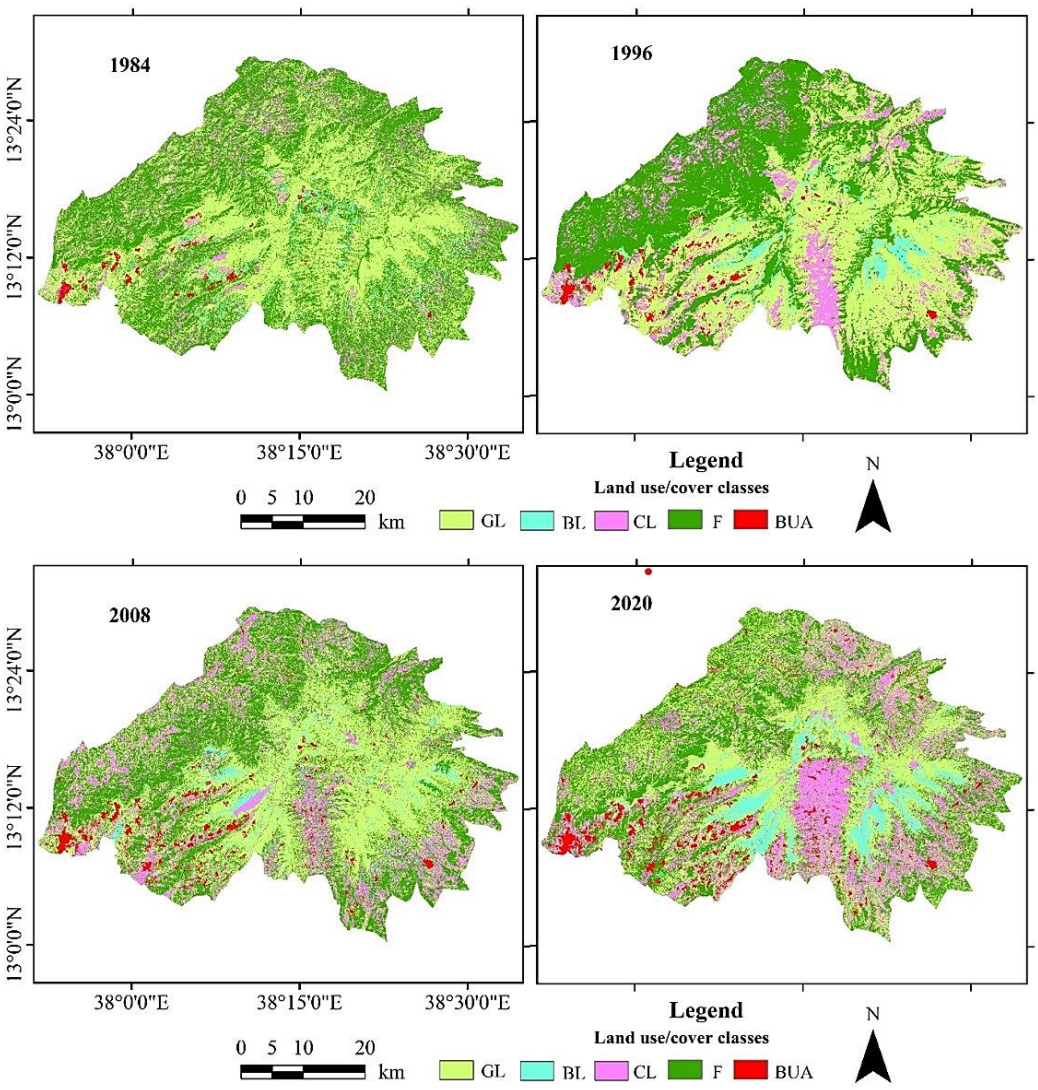


Figure 6: Classified land cover map from 1984 to 2020.

The trend analysis for three consecutive periods (1984–1996, 1996–2008, and 2008–2020) showed spatiotemporal changes in the LC types. A comparison of the three study periods revealed that cultivated land increased at a rate of 3.7% (1984–1996), 2.3% (1996–2008), and 3.6% (2008–2020), at a rate of 971 ha year^{-1}, 884 ha year^{-1}, and 928 ha year^{-1}, respectively (Figure 7). Similarly, bare land and built-up areas increased at higher rates than cultivated land in the three study periods. Conversely, substantial forest cover and grassland reductions were observed during the entire study period.

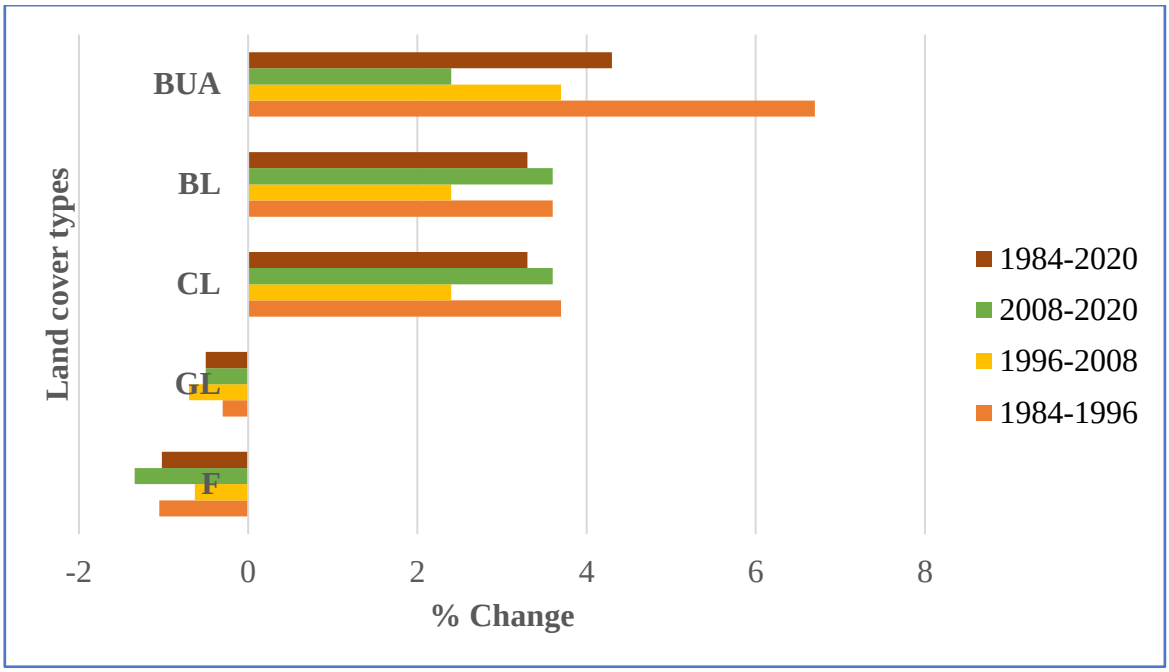


Figure 7: Percentage of change in each land cover type.

2.3.3. Forest Cover Change

Table 7 shows the trends and rate of forest cover change in the study area. The results indicated that between 1984 and 2020, about 33,094 ha of forest was cleared, which is 31% of the forest cover in 1984. This translated to around 919 ha (1.02%) of forests being deforested annually. However, the highest rate of deforestation was observed during the third period, i.e., in 2008 (−1.34%), followed by the first period (–1.05%). According to experts, the reduction of forest cover during the first period (1984–1996) was most likely attributed to the civil war between the Derge and the current government, drought, and growing demand for forest products by the communities residing in the study site.

Nevertheless, the reduction in forest cover during the second period (1996–2008) was attributed to changes in the regime. When the present government came to power, large, forested areas were converted into agricultural land, particularly during the transition, contributing to forest loss. Similarly, in contrast to the 2007 forest development, conservation, and utilization policy and strategy, forest resources in the study area declined substantially in the third period (2008–2020). Several factors could contribute to this, including the growing demand for farmland, fuelwood and residential areas, rapid population growth, weak institutional arrangement, and forest fire. Local elders and experts also confirmed this during the interview.

Table 7: Annual rate of deforestation in ha and % (1984-2020).

Study period	Annual rate of deforestation (in ha)	Annual rate of deforestation (in%)
1984-1996	-1,075	-1.05
1996-2008	-583	-0.63
2008-2020	-1,099	-1.34
1984-2020	-919	-1.02

2.3.4. Land Cover Inter-Category Transition

Table 8 presents the change detection matrix of various LC types in the study area from 1984 to 2020. The diagonal entries in Table 8 show the amount of LC types that remain unchanged (persistence) between the study periods. In contrast, the off-diagonal entries revealed the column 'gain' and row 'loss', indicating the increase or decrease in a particular LC type. Although all LC classes have changed, the degree of these changes was inherently different. Accordingly, the results show that about 38% (92,049 ha) of the study area persisted while 62% (149,044 ha) changed in one way or another between 1984 and 2020, indicating that the study area experienced substantial LC change. Furthermore, the analysis results from different periods revealed that most of these changes were non-linear and dynamic. For instance, forests lost the most (65,898 ha) during the study period, while cultivated land gained the most (49,547 ha) of the total land cover in the study area. Similarly, they showed a comparatively equal magnitude of net change (−33,082 ha and +33,387 ha) but in opposite directions.

Table 8: "From-to" transition matrix (ha) resulting from change detection analysis.

1984-2020	BL	BUA	CL	F	GL	Total 1984	Loss
BL	**108**	275	1092	2040	1074	4591	4481
BUA	8	**1705**	4	11	11	1739	34
CL	395	722	**4844**	7002	8043	21004	16162
F	1732	2847	24759	**42384**	36560	108282	65898
GL	12470	2545	23692	23763	**43008**	105477	62470
Total 2020	14713	8095	54392	75200	88696	241093	149045
Gain	14605	6389	49547	32816	45688	149045	

The change detection matrix revealed that out of 108,282 ha of forests in 1984, only 42,384 ha remained unchanged in 2020, implying that about 65,898 ha (61%) of forests were converted into various LC types, and the largest conversions were made into grassland (36,560 ha), followed by cultivated land (24,759 ha). The results also revealed that the total gain in forest cover from other LC types was about 32,816 ha, with a negative net change of

33,082 ha. These observed spatial and temporal changes in forest cover were attributed to the increasing demand for fuelwood and charcoal, farm plot expansion and grazing lands, construction materials, and farm implements, as reported by elders and experts during the interview.

The matrix also displayed that during the study period, out of 105,477 ha of grassland in 1984, about 43,008 ha remained as grassland in 2020, indicating that some 62,470 ha were converted to other LC types. However, it gained about 45,688 ha from other LC types, with a negative net change (−16,782 ha) with varying degradation levels. According to local elders, grassland has been significantly reduced over time due to the illegal expansion of cultivated land, grazing lands, and settlements. Similarly, interviews with experts and development agents confirmed that population growth and associated cultivated land encroachment, as well as uncontrolled livestock grazing, could be possible causes of grassland loss in all directions of the SMNP.

In contrast, the proportion of cultivated land increased consistently throughout the study period. The change detection analysis confirmed that 4,844 ha of the total 21,004 ha of cultivated land in 1984 remained as cultivated land, indicating that 16,160 ha were converted to other LC types. The results also show that cultivated land gained a total of 49,547 ha, with a net positive change of 33,388 ha. Of these, 24,759 ha and 23,692 ha originated from forest and grassland, respectively. Similarly, over the last 36 years, bare land has increased in the study area. According to the change detection analysis, only 108 ha of the 4,591 ha of bare land in 1984 remained unchanged in 2020, while about 97.6% of the bare land had been converted into forests (2,040 ha), cultivated land (1,092 ha), and grassland (1,074 ha). However, gains in grassland and forest more than offset the loss of bare land. The overall gain in bare land from other LC types was about 14,605 ha. As highlighted by participants during the KII, the increase in the bare land was probably attributed to rapid deforestation and overgrazing, which removed the natural vegetation cover from the land and rendered it barren and exposed rock.

The built-up area was the other LC type that experienced considerable area increment during the study period. The results revealed that, of the 1,739 ha of built-up area in 1984, about 1,705 ha remained unchanged during the study period, suggesting that only 34 ha were converted into other LC types. The change detection matrix also revealed that the built-up area gained (6,389 ha) from all other LC types, primarily from forests and grasslands but

experienced the lowest conversion into other LC types. According to key informants, the rapid expansion of built-up areas can be attributed to road construction, institutions, and increasing demand for residential areas.

Furthermore, Figure 8 illustrates the conversion of LC types observed from one class to another between 1984 and 2020. The post-classification results revealed that the study area experienced deforestation, rehabilitation, and no change. First, the previously categorized five LC classes were reclassified into forest and non-forest to analyze the change from forest to non-forest and vice versa. In this instance, the classes of grassland, cultivated land, bare land, and built-up area are all regarded as non-forest, but the forest class has remained. Then, a change detection analysis is performed. As shown in Figure 8, deforestation, rehabilitation, and no change describe the transition from forest to non-forest, non-forest to forest, and non-forest to non-forest/forest to forest, respectively.

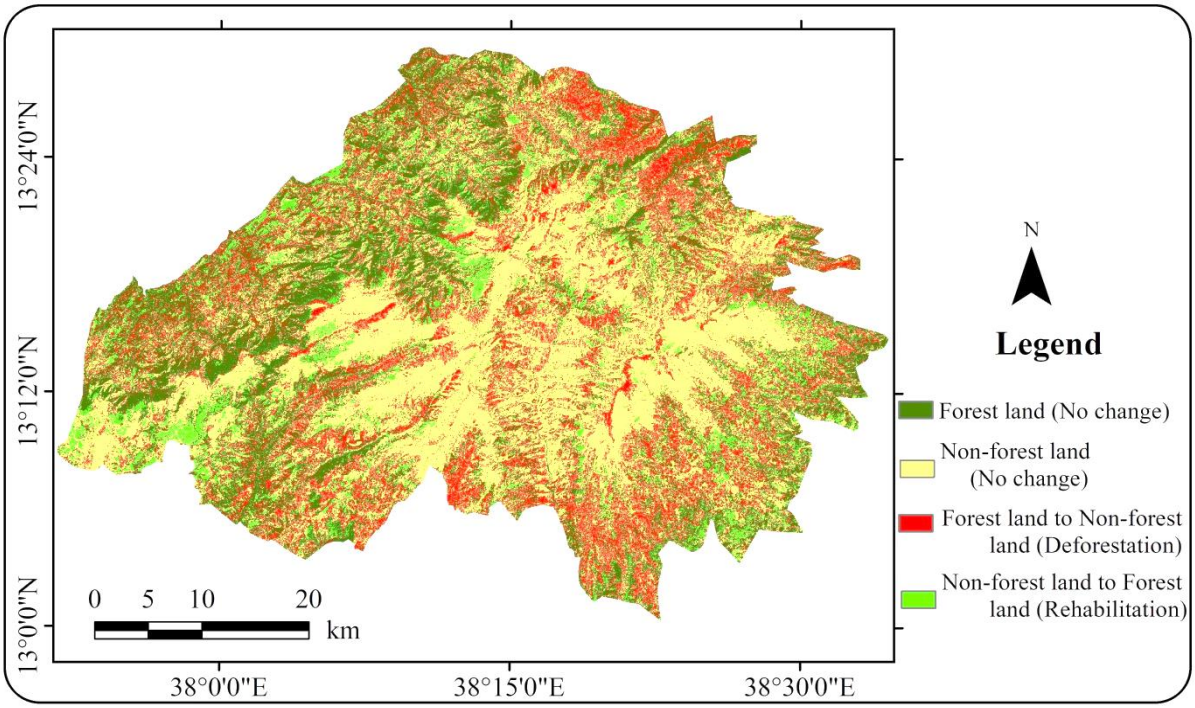


Figure 8: Land cover changes in the study area between 1984 and 2020.

2.3.5. Net Change and Swap in and around the SMNP

Table 9 shows the changes attributed to swap and net change. The results revealed that the highest persistence was observed for grassland (17.8%), followed by forests (17.6%) between 1984 and 2020. Similarly, cultivated land and forests experienced relatively more gains and losses (Table 9). The results further revealed that most of the LC in the study area had experienced swap changes. Changes in the built-up area were only a net change

throughout the entire study period (1984–2020), whereas changes in all other LC types were a combination of swap and net changes. The change attributed to quantitative net change was highest for cultivated land (51% of the total change for cultivated land), followed by forests (33.5% of the total change for forests). Net change accounted for about 34% of the total change in and around the SMNP. However, in the study area, the changes attributable to location (swap) were highest for grassland (84% of the total change for grassland), followed by forest (66.5% of the total change for forest).

Table 9: LULC Change (in %) gain, loss, swap and absolute net change in the SMNP.

LC types	Total 1984	Total 2020	P	G	L	TC	S	NC	G_p	L_p	N_p
BL	1.9	6.1	0.1	6.0	1.9	7.9	3.72	4.2	60	19	42
BUA	0.7	3.4	0.71	2.7	0.01	2.7	0.03	2.64	3.8	0.01	3.7
CL	8.7	22.6	2.01	20.6	6.7	27.3	13.4	13.85	10.2	3.3	6.9
F	44.9	31.1	17.6	13.6	27.3	40.9	27.2	13.7	0.8	1.6	-0.8
GL	43.7	36.8	17.8	19.0	25.9	44.9	37.9	6.96	1.1	1.5	-0.4
Total	100.0	100.0	38.2	61.8	61.8	61.6	41.1	20.7			

P: persistence, G: gain, L: loss, TC: total change, S: swap, NC: net change, Gp: gain-to-persistence, Lp: loss-to-persistence, and Np: net change-to-persistence.

Similarly, grasslands experienced the highest total change (45%), followed by forests (41%) and cultivated land (27%). Of the total forest cover, about 67% could be attributed to swap changes. Higher values of swap indicate features of ecological damage and restoration simultaneously but in different locations. In the study area, the changes attributable to location (swap: 41.1%) are greater than those attributable to quantity (net change: 20.7%), demonstrating the importance of net change and swap in identifying the total transition within the study area.

2.3.6. Vulnerability of SMNP to Transition

Table 9 also presents the vulnerability of LC types to transition in the study area. The results revealed that except for the built-up area, the loss-to-persistence (L_p) ratio for all LC types was greater than 1. This implies that all the LC types in the study area tended to change to other LC types more than persisting. However, the L_p ratio for the built-up area was less than 1, indicating that the LC type tends to persist rather than lose. Furthermore, the gain-to-persistence (G_p) ratio was greater than 1 for all LC types except forests, suggesting that most LC types tended to grow compared to their original extent. However, the Gp ratio of the forest is less than 1, implying that forest cover has experienced deforestation. Similarly, the

net-change-to-persistence (N_p) ratio for forest and grassland was negative, indicating that these LC types are more likely to lose their areas than other LC types. Conversely, the N_p ratios of cultivated land, bare land, and built-up areas were relatively high, signifying their persistence compared to their net loss.

2.3.7. Drivers of Forest Cover Changes

Linking remote sensing results with the KII and household surveys allows us to examine the drivers of forest cover change. Accordingly, many intertwined and connected factors, some natural but mostly anthropogenic, exacerbate deforestation. From household surveys and KII, six drivers were identified as the main drivers of forest cover change in the study area (Table 10). As reported by key informants and surveyed households, the expansion of subsistence agriculture to meet the food needs of the growing population has been one of the leading causes of deforestation in the study area. The results revealed that 98% of the surveyed households viewed agriculture expansion as the primary driver of deforestation.

Table 10: Drivers of Forest Cover Change in and around the SMNP.

Variables	Label	%	Rank
Drivers of forest cover loss*	Agricultural land expansion	98	1
	Fuelwood collection	75	2
	Population growth	65	3
	Livestock pressure	60	4
	Forest fire	17	5
	Weak law enforcement	14	6

Source: Field Survey (2021); *multiple responses

Similarly, the remote sensing analysis confirmed that agricultural land had expanded significantly from 8.7% in 1984 to 22.6% in 2020 at the expense of forests, implying 24,759 ha of forests converted to agricultural land. In addition, biomass, particularly fuelwood harvesting for domestic use, is the second driver of deforestation mentioned by 75% of the surveyed households. The SMNP and adjacent communities rely on biomass fuel to meet their energy needs. However, as confirmed by experts, the steadily growing demand for fuelwood, the slow development of rural electrification, and the limited availability of alternative energy sources have resulted in unsustainable forest exploitation. The local elders also confirmed during the interviews that the population in and around the SMNP has a low income and lacks alternative means of subsistence. Hence, harvesting and selling fuelwood and charcoal is an easy and quick way to make a living, contributing to deforestation.

On the other hand, surveyed households and key informants reported population growth as an important driver of deforestation. According to the central statistical agency (CSA), the population in and around the SMNP has increased from 157,779 in 1984 to 378,929 in 2020, representing a 140% increase. As the population grows, demand for agricultural land, residential areas, fuelwood, and other forest products increases, putting enormous pressure on forest resources. Hence, the results revealed that 65% of surveyed households perceived population growth as the third driver of deforestation. In addition, livestock pressure was mentioned by 60.4% of the respondents as the fourth driver of deforestation. Free grazing is a significant problem for vegetation resources in areas with a high livestock population, like the SMNP and adjacent districts. This is a problem since vegetation is a valuable source of fodder for livestock, especially during the dry season. Consequently, livestock pressure has accelerated the rate at which forests and grass species are becoming scarce, as experts confirmed. Furthermore, surveyed households have reported forest fires occasionally occurred, particularly during the dry season, and are viewed by 17% of the surveyed households as another driver of deforestation. Locals also claim that the fire started when clearing debris on their farm plots and during honey harvesting; however, it quickly spread to the forests and grasslands, resulting in deforestation.

2.3.8. Impacts of Forest Cover Change on the Availability of Forest Services

Declining forest cover has far-reaching impacts on the availability of forest products and services in the study area. The results revealed that 92% of the surveyed households perceived a change in forest ecosystem services availability, while only 8% did not perceive changes (Table 11).

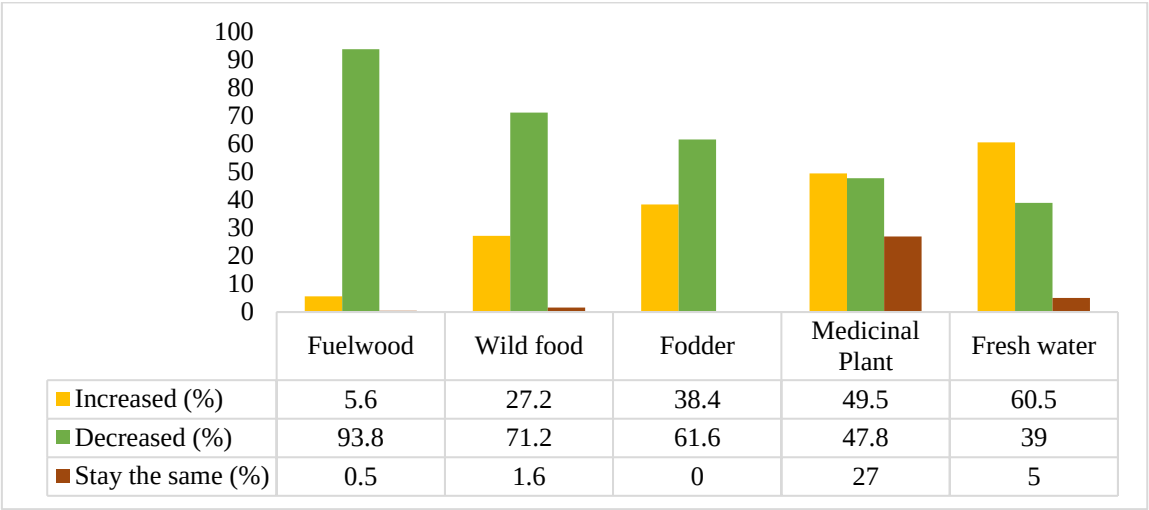
Table 11: Households' perception of the change in the availability of forest services

Perception of changes in forest ecosystem services getting from the Semien Mountains forest resources	Label	N	%
	Yes	372	92.3
	No	31	7.7
Households using fuelwood for domestic uses (in %)			87
Average time spent to collect fuelwood (in minutes)			168
Average distance to the forest resources (in minutes)			69

Source: Field survey (2021)

In addition, the results revealed that five ecosystem services provided by the Semien Mountains forests were highly impacted by deforestation (Figure 9). About 94% of the surveyed households reported that deforestation has reduced fuelwood availability. Similarly, 87% of the surveyed households use fuelwood for domestic purposes (Table 11).

Because of this reason, the Semien Mountains forests have significantly been deforested, leading to fuelwood scarcity. Moreover, according to elders and experts, deforestation by the growing population has resulted in a decline in fuelwood availability. The results revealed that the average travel time (round trip) to collect fuelwood ranged from 1 h to more than 8 h, with an average of about 3 hours (Table 11). Furthermore, surveyed households reported that deforestation had reduced the availability of wild food (71.2%), fodder (61.6%), and freshwater (39.2%) derived from the Semien Mountains. Overall, deforestation exacerbates soil loss, fuelwood scarcity, flooding, biodiversity loss, climate-induced drought, and economic loss, as reported by experts during the interview.



	Fuelwood	Wild food	Fodder	Medicinal Plant	Fresh water
Increased (%)	5.6	27.2	38.4	49.5	60.5
Decreased (%)	93.8	71.2	61.6	47.8	39
Stay the same (%)	0.5	1.6	0	27	5

Figure 9: Availability of forest services in the SMNP.

Source: Household Survey (2021).

2.4. Discussion

The Semien Mountains forests provide various socio-economic, ecological, and environmental benefits locally, regionally, and globally but the local community benefits the most (Jacob et al., 2017). However, the analysis reveals that the forests had experienced spatiotemporal changes over the last 36 years, resulting in a loss of about 33,084 ha of forest. As a result, the capacity of these forests to provide forest benefits and services to society is sustainably threatened by continuous deforestation. Changes in forest cover jeopardize ecosystem services, including fuelwood availability, climate regulation, biodiversity conservation, and water catchment protection (Bewket, 2002; Gebrehiwot et al., 2014; Chaudhary et al., 2017; Ahammad et al., 2019; Agariga et al., 2021). In contrast, agricultural land and built-up areas increased by 33,387 and 6356 ha, respectively. This makes the

expansion of agricultural land and built-up areas the two most dominant causes of deforestation in the study area.

The conversion of a large portion of forest resources into cultivated land by smallholder farmers has been reported throughout Ethiopia (Hailemariam et al., 2016; Deribew & Dalacho, 2019), and this has occurred in and around the SMNP as well (Jacob et al., 2017). During the last 36 years, about 24,759 ha of forests have been converted into farmland in the study area. The remote sensing analysis also revealed that an estimated 927 ha of cultivated land was added each year, primarily from forests. Between 1984 and 2020, the annual rate of deforestation was 1.02%, which is very close to Ethiopia's estimated annual deforestation rate of 1.1% (FAO, 2010a), implying that the forest in the study area is prone to cultivation. Similar to the present study, previous studies conducted in various parts of Ethiopia (Gebrehiwot et al., 2014; Worku et al., 2016; Miheretu & Yimer, 2017; Belay & Mengistu, 2019) and elsewhere in developing countries (Suleiman et al., 2017; Ahammad et al., 2019; Munthali et al., 2019; Agariga et al., 2021) documented a reduction in forest cover owing to agricultural expansion. However, in contrast to previous and current findings, an increase in forest cover was observed in Ethiopia's highlands (Bewket, 2002; Belayneh et al., 2018; Moges & Bhat, 2018). The deviation could be attributed to management practices, a change in the definition of forest, and the study's spatial coverage.

However, expanding agricultural land often comes with many environmental costs as it is practised without proper land management (Belay & Mengistu, 2019). The rapid expansion of agricultural lands at the expense of forests severely impacts land resources. For instance, the European Union Delegation to Ethiopia EUDE (2016) reported that in the deforested highlands of Ethiopia, the topsoil has already been substantially degraded, causing the soil depth to drop to less than 10 cm, which in turn hinders crop productivity. Hailemariam et al. (2016) reported that an estimated 30,000 ha of productive land is lost in Ethiopia's highlands due to soil erosion. Similarly, WBISPP (2005) stated that the annual production lost due to soil erosion in the ANRS alone is about 10,000 tons. In agreement with the finding of this study, studies conducted elsewhere in the Ethiopian highlands (Hailemariam et al., 2016; Agidew & Singh, 2017; Miheretu & Yimer, 2017; Suleiman et al., 2017; Gebrehiwot et al., 2021) documented that agricultural land expansion aggravates land degradation and affects the livelihoods of local communities.

The other LC type that experienced a substantial change in and around the SMNP was bare land, which increased by 220% between 1984 and 2020. According to the experts during the interview, the increase in bare land was due to the volcanic and rocky nature of the mountains as well as continued deforestation and overgrazing. This finding is consistent with the findings of (Agidew & Singh, 2017; Hassen & Assen, 2017; Miheretu & Yimer, 2017) but differs from (Worku et al., 2016; Ewunetu et al., 2021), who both reported a decrease in bare land.

Furthermore, the built-up areas showed a considerable increase in cover. The overall expansion of the built-up area has been 6,356 ha (365% ha), owing to natural population increase, infrastructural development, and increased demand for the residential area, as confirmed by locals and experts during the interview. This finding is in line with the findings of (Miheretu & Yimer, 2017; Moges & Bhat, 2018), who documented that built-up areas were rapidly expanded at the expense of forests and grasslands.

A broad range of drivers of forest cover changes is observed in different parts of the world. The drivers of change are time and location-specific (Ewunetu et al., 2021). A driver identified a decade ago may not be valid in recent times if intervention measures are made regarding the driving factors (Munthali et al., 2019). Many, if not most, land cover changes are intended or unintended consequences of human decisions and subsequent actions (Geist & Lambin, 2001). Dynamic drivers contributing to forest loss in different social and ecological contexts have been reported by various studies in Ethiopia (Gebrelibanos & Assen, 2015; Zewdie & Csaplovics, 2015; Belayneh et al., 2018; Deribew & Dalacho, 2019; Yesuph & Dagnew, 2019; Ewunetu et al., 2021) and elsewhere in developing countries (Geist & Lambin, 2001; Ahammad et al., 2019; Munthali et al., 2019).

Geist and Lambin (2002) highlighted that tropical deforestation occurs due to direct and indirect drivers. Direct drivers of deforestation include anthropogenic activities or immediate actions that directly impact forest cover and loss of carbon, like agriculture, urban expansion, mining, livestock grazing, and forest fires (Rotich & Ojwang, 2021). The indirect drivers encompass complex interactions of fundamental political, socio-economic, cultural, and technological processes: corruption, poor governance, population growth and land tenure uncertainties (UN, 2017; Rotich & Ojwang, 2021). Hence, understanding the drivers of deforestation is fundamental for developing policies and measures to alter current trends in forest activities toward a more climate and biodiversity outcome (Hosonuma et al., 2012).

Based on the results of key informants and household surveys, several factors contributed to the change in forest cover in the study area over the last 36 years. According to the study, the most important cause of deforestation was population growth, along with agricultural expansion. Though the impact of population growth on forest cover is controversial, rapid population growth drives forest cover change (Belay & Mengistu, 2019). In their study, Geist and Lambin (2001) estimate that population growth is responsible for 61% of tropical deforestation. Additionally, Bremner et al. (2010) showed that population growth contributes to deforestation. Our study revealed that the study area's population has more than doubled in the last 36 years, thus increasing the demand for agricultural land and food. A study by Wondie et al. (2016) concluded that land conversion is an immediate solution to meeting the food demand of the country's rapidly growing population. Since agriculture is the main livelihood in the study area, the conversion of most of the natural vegetation cover into farmland is a peculiar phenomenon. In line with this finding, studies conducted in Ethiopia's highlands (Bewket, 2005; Worku et al., 2016; Agidew & Singh, 2017; Ewunetu et al., 2021) reported that population growth is a cause for concern for forest destruction.

Moreover, fuelwood collection is another significant driver of forest cover change in the study area between 1984 and 2020. Biomass, particularly fuelwood, is an invaluable source of energy for local communities in the study area. The demand for biomass has increased over the past few decades as the population has grown. According to Bewket (2005), this demand is related to traditional three-stone open-fire stoves for cooking and baking, which forces communities to use more fuelwood, contributing to deforestation and fuelwood scarcity (Damte & Koch, 2011). As a result, natural vegetation has significantly diminished and is currently found only in a few remote mountainous areas. Our study's findings agree with those of previous studies conducted in the highlands of Ethiopia (Bewket, 2005).

Similarly, livestock pressure and poor management of grazing areas also contribute to forest loss. Based on satellite image analysis (Table 4), grasslands have receded over the last 36 years since natural grasslands are the major feed sources for livestock. A study conducted by EWCA (2015) reported that an estimated 129,270 Tropical Livestock Units (TLUs) reside in and around the SMNP, which translates to an average of 7 TLUs. As a result, overgrazing would occur, threatening the remaining grasslands and forests. This finding agrees with (Moges & Bhat, 2018; Yesuph & Dagnew, 2019), who found that livestock ranching contributes to the loss of vegetation cover.

Furthermore, forest fires occasionally occur in the study area during the dry season. As reported by key informants during the interview, the fires originate from slash-and-burn land preparation methods, using fire during honey harvesting and the burning of grazing land to allow for pasture regeneration, contributing to a decline in forest cover and biodiversity loss. This result is in agreement with the findings of (Zewdie & Csaplovics, 2015; Rotich & Ojwang, 2021), who reported that fires contribute to the loss of forests and biodiversity.

2.5. Implications of Forest Cover Change

Forest cover changes are an inevitable and complex phenomenon with multifaceted socio-economic and ecological effects (Ahammad et al., 2019). The conversion of vegetation, the habitat of animals and microbes, into agricultural and other land-use types poses the greatest threat to biodiversity loss due to forest cover change (Yesuph & Dagnew, 2019). According to key informants, multipurpose indigenous tree species, such as *Juniperus procera*, *Hagenia abyssinica*, and *Olea Africana*, once found in the Semien Mountains and adjacent districts, are on the verge of extinction due to deforestation. These indigenous trees can currently be found only in protected areas and inaccessible steeper mountainous areas (Asrat et al., 2012). Similarly, as forest and grassland cover declines, so does the number of wild animals (ANRS, 2007). According to key informants, wild animals such as leopards and antelope were common in the study area 36 years ago. However, the conversion of forest and grassland to cropland and other land uses has decreased the number of these wild animals. In addition, deforestation may affect the ecosystem services provided by forests, such as the decline of direct benefits of wild food, fuelwood, construction materials, and biodiversity (Ahammad et al., 2019). Moreover, it indirectly contributes to the loss of soil fertility, degradation of freshwater resources, and emission of carbon (Köhl et al., 2015; Miura et al., 2015; Abir & Saha, 2021).

2.6. Conclusions

Monitoring forest cover change and identifying its drivers have immense potential for decision-making, sustainable management, and policy development. Using multitemporal Landsat images coupled with household surveys and KIIs, this study examined spatiotemporal forest cover change and its drivers in and around the SMNP from 1984 to 2020. In data-scarce situations, the study used simple but important techniques to offset the limitations of the coarse-resolution Landsat images and improve the accuracy of the mapping of forests. Since the SMNP is very rugged and mountainous, topography affects the

reflectance due to illumination effects and cast shadows, which introduce errors in LC classification. In addition, a significant portion of the area in the Landsat 7 image of 2008 was affected by scan line corrector failure. Hence, we employed C-correction to correct topographic effects. Similarly, Landsat toolboxes in ArcGIS 10.8 was applied to fix scan line errors.

According to the image classification, the SMNP has experienced spatiotemporal forest cover change over the past 36 years. Between 1984 and 2020, about 33,084 ha of forest were cleared, accounting for 31% of the forest cover in 1984. In other words, about 919 ha (1.02%) of forests are deforested annually. In contrast, farmland, bare land, and built-up areas increased from 9%, 2%, and 1% in 1984 to 23%, 6%, and 3% in 2020, respectively. This implies that the increase in farmland, bare land, and built-up areas results from deforestation and grassland conversion. The observed reduction in forest cover was driven by many intertwined factors, including population growth, growing demand for farmland and fuelwood, livestock pressure, and forest fires.

The change analysis matrix revealed that 62% of the study area had experienced a change, while 38% of the landscape remained unchanged. Specifically, the change matrix showed that forests lost the most (65,898 ha) while cultivated land gained the most (49,547 ha) of the total LC in the study area. On the landscape, the change attributable to location (swap: 41%) is greater than the change attributable to quantity (net change: 21%). Moreover, the spatial pattern of change revealed that forest cover experienced both swap and net change. From 1984 to 2020, there was a net change of 14% and a total change of 41% in forest cover. Over the same period, swap changes accounted for about 67% of the forest cover changes.

Overall, the Semien Mountains forests deserve much attention since it is home to endangered endemic species, including the iconic and severely endangered Walia ibex (*Capra walie*) and Ethiopian wolf (*Canis simensis*), found only in the SMNP. The result of this study can guide government, community, and stakeholders in their conservation and restoration efforts by focusing on the degradation of hotspots. Improving local communities' awareness of the co-existence of nature conservation and sustaining their livelihood, disseminating improved cookstoves, and enhancing participatory forest management are possible solutions to reduce the pressure on the forest resources of the Semien Mountains. Finally, the study recommends further research to investigate the impact of forest cover change on the forest ecosystem service value and the socio-economic well-being of adjacent communities.

CHAPTER THREE: DETERMINANTS OF HOUSEHOLD ENERGY CHOICE FOR DOMESTIC CHORES: EVIDENCE FROM THE SEMIEN MOUNTAINS NATIONAL PARK AND ADJACENT DISTRICTS, NORTHWEST ETHIOPIA

ABSTRACT

Energy is a cornerstone and strategic tool to meet basic human needs and address many global development challenges. However, ensuring energy supply while limiting energy's contribution to environmental change is a major challenge confronting the energy sector in many developing countries. The challenge is more severe in Sub-Saharan Africa, where about 900 million people still rely on biomass fuels for cooking. Cooking with biomass might not be a problem by itself. Instead, it is the inability to use biomass energy resources sustainably. Improving the opportunities for modern and sustainable energy use is, thus, an essential prerequisite to enhancing the livelihoods of the poor. This study examines the determinants of household energy choice in the Semien Mountains National Park and adjacent districts in Northwest Ethiopia. A survey of 420 randomly selected households was administered using a semi-structured questionnaire. Descriptive statistics and a multivariate probit model were employed to analyze the data. Results showed that households' energy utilization pattern is skewed towards biomass fuels, particularly fuelwood (87%), while only a few households use charcoal (32%) and electricity (17%) for domestic chores. The study also shows that the majority (87%) of households collect all of their energy sources themselves, while 13% purchase from the market. In addition, the results show that about 77% of households perceived that fuelwood availability had decreased over time owing to deforestation. Estimates of the multivariate probit model showed that a mix of factors, including age, gender, household size, education, income, access to electricity, off-farm activities, access to market, distance to forest, and housing type, determine household cooking energy choice and the extent of dependency on it. Thus, the findings proved that local communities prefer fuel stacking rather than ascending the energy ladder. Based on the results, the study recommended that the local community be encouraged to use biomass fuels in a more environmentally friendly way and use sustainable and affordable modern energy sources.

Keywords: Biomass, Energy, Energy ladder, Fuel choice, Fuel stacking, Multivariate probit

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3.1. Introduction

Energy is a cornerstone and strategic tool to attain basic human needs and address many global development challenges (Kowsari and Zerriffi, 2011; Nussbaumer et al., 2012; IEA, 2018; Martey, 2019). Most development goals, including the Sustainable Development Goals (SDGs), demand a sustainable supply of energy resources that is sustainably available at a reasonable cost and can be utilized for all required tasks without causing negative societal and environmental impacts (Sopian et al., 2011). However, ensuring energy supply while limiting energy's contribution to environmental change is a major challenge confronting the energy sector in many developing countries (Kaygusuz, 2011).

The problem is more severe in Sub-Saharan Africa (SSA), with some 890 million people still relying on traditional biomass fuels for their basic energy needs (IEA, 2018). This is a cause of concern because biomass fuels have severe consequences on human health and the environment at large (Twumasi et al., 2020). A recent study by Imran et al. (2019) indicates that burning biomass fuel directly in open fires causes indoor air pollution (IAP) that harms the health of women and children. According to WHO (2018), nearly 4 million people die yearly from IAP exposure to inefficient cooking practices. Aside from health concerns, burning biomass fuels contribute to climate change by emitting CO_2 into the atmosphere (Muller and Yan, 2018). This further damages agricultural productivity (Pandey and Chaubal, 2011) and threatens the nutritional health of human beings (Muller and Yan, 2018).

As Van Der Kroon et al. (2013) pointed out, biomass fuel usage in traditional and inefficient cooking stoves requires more fuel, thereby putting a burden on women and children to allocate extra collection time (Foell et al., 2011; Karimu, 2015). These practices prevent women and children from earning a living or pursuing education, respectively (Lewis and Pattanayak, 2012). Unsustainable fuelwood harvesting further degrades local forests and woodlands, all of which contribute to land degradation and climate change (Foell et al., 2011). Switching to modern fuels, therefore, provides many potential benefits, such as improving the welfare of women by providing them with the opportunity to engage in income-earning activities as a consequence of the efficiency and reduced time required for cooking (Karimu, 2015). In light of the issues associated with energy, it is important to understand the key variables that influence household fuel choice and transition (Twumasi et al., 2020), which will help policymakers formulate and promote appropriate energy policies to support energy transition.

Ethiopia, with a population of 115 million in 2020, is Africa's second-most populous country after Nigeria (PRB, 2020). Providing adequate energy sources for the country's growing population is a challenge now and in the future. Economic development requires increasing energy demand, but limited access to affordable and clean energy remains an important barrier to achieving development goals (Mondal et al., 2018). Ethiopia is potentially endowed with a variety of energy sources: hydropower, wind, solar, geothermal as well as biomass (Mondal et al., 2017). However, these have not yet been developed to economically optimal levels, and many households are experiencing severe energy problems (Mengistu et al., 2016). Ethiopia, for example, lags behind other SSA countries in many ways, including energy. In 2017, modern energy: electricity shared approximately 13% of the total energy consumption (Tiruye et al., 2021). Per-capita electricity consumption was about 93 kWh per year, which is significantly lower than the average per capita energy consumption in SSA (521 kWh/capita/year) (MoWE, 2012). Moreover, according to the Multidimensional Energy Poverty Index report, Ethiopia scored 0.9, indicating severe energy poverty (Nussbaumer et al., 2012).

Ethiopia has faced several challenges as it has strived to promote modern and clean energy at the household level. Biomass is Ethiopia’s primary energy source, accounting for about 88% of the total energy supply (Tiruye et al., 2021). Apart from biomass, other primary energy sources include electricity and petroleum, collectively accounting for 9.3% (Mondal et al., 2018). Household is a primary energy-consuming sector, accounting for 88% of total energy consumption in Ethiopia (Getie and Degefa, 2019; Pappis et al., 2021; Tiruye et al., 2021). The primary end-use of biomass fuel is for domestic cooking and baking (MoWE, 2012), which accounts for over 60% of household energy consumption (Gebreegziabher et al., 2012).

Various studies have shown that excessive reliance on biomass fuel negatively affects the environment as it causes deforestation (Guta, 2014; Gebreegziabher et al., 2017). Between 1990 and 2010, for instance, the average annual rate of deforestation in Ethiopia was nearly 1% (FAO, 2010a), which is one of the highest in the world, and household energy utilization patterns, particularly fuelwood use, play a significant role (Tucho and Nonhebel, 2015). As a result of indiscriminate felling and exploitation of trees for fuel, greenhouse gas emissions are expected to increase from 24 Mt of CO_2 in 2010 to 41 Mt of CO_2 in 2030 if no action is taken (FDRE, 2011). Besides, the excessive use of fuelwood leads to ecological imbalance

and degradation of forest cover without regeneration (Negash and Kelboro, 2014), which in turn has led to millions of populations suffering from energy scarcity (Guta, 2014)).

In response to the challenge to access and low household consumption of modern and clean energy sources, the Government of Ethiopia has clearly outlined its path to accessing modern and clean energy sources in its medium-term development plans (GTP-I and GTP-II) (FDRE, 2019). The plan has remained relevant in transforming the landscape of household energy consumption and preferences to build and disseminate renewable energy technology (Marie et al., 202; Tiruye et al., 2021). However, despite the policy giving priorities, consumption of modern and clean energy sources remains relatively low at the household level. Moreover, the Government, in conjunction with Non-Government Organizations (NGOs) and donors, has made significant efforts to increase access to and use of modern and clean energy sources (FDRE, 2011). Accordingly, rural electricity coverage has increased from 2% in 2000 to 33% in 2018 (IEA, IRENA, WB, WHO, 2020), and the dissemination of fuel-efficient cooking stoves has grown (>10%) in recent years (MEFCC, 2018). However, despite recent advances in modern and clean energy in Ethiopia and the ANRS, substantial knowledge gaps persist regarding the determinants of household energy choices and factors that hinder the transition to modern fuels.

Amhara region is suffering from a significant domestic energy crisis, which can be seen in its relatively low per capita energy intake (Marie et al., 2021). About 90% of the households in the region use traditional biomass fuels as their main cooking energy source, and about 10% use electricity from hydroelectric power (Asres, 2012). The inaccessibility and unaffordability of modern fuel and associated problems are more pronounced in the region (Getie and Degefa, 2019). Various interrelated economic and non-economic factors influence household cooking fuel choices in the ANRS and elsewhere in Ethiopia (Abebaw, 2007; Getie and Degefa, 2019; Wassie et al., 2021). Previous studies (Mekonnen and Köhlin, 2009; Gebreegziabher et al., 2012; Alem et al., 2016) mainly focused on analyzing the determinants of household cooking fuel choice of a single fuel type rather than jointly estimating the probability of choosing multiple fuel types simultaneously. However, households use multiple fuels for cooking activities as it provides users with energy security. A better understanding of factors that hinder the transition to modern fuels, understanding the drawbacks of traditional fuel consumption, and identifying factors influencing household cooking fuel choice will be critical for recommending energy development pathways for the country. Thus, this study aimed to examine the determinants of household cooking fuel

choices and transitions among households residing in the Semien Mountains National Park (SMNP) and adjacent districts in Northwest Ethiopia.

3.2. Theoretical Literature and Conceptual Framework

The theory of household fuel choice is founded on two widely used theories: the energy ladder and fuel stacking models (Masera et al., 2000). The energy ladder model views household fuel choices as a progression that corresponds to income growth, as well as a hierarchical order from traditional fuel to transitional fuel and eventually to modern fuels (Heltberg, 2005; Rahut et al., 2017; Giri and Goswami, 2018; Shallo et al., 2020). Further, the model described a linear and unidirectional progression of fuel adoption, claiming that moving up the ladder means abandoning the fuel at the lower level (Kowsari and Zerriffi, 2011). This model contradicts field research findings and is criticized by many studies for emphasizing income as a determinant of household fuel choice (Masera et al., 2000; Heltberg, 2004). Many recent studies have theorized household fuel choice from the perspective of fuel stacking. According to the fuel stacking model, energy choice and household transition do not always imply a stepwise transition from one fuel to another (Mensah and Adu, 2015). Instead, households combine various energy sources for multiple end-uses, and fuel choices are not mutually exclusive because households can use any combination of fuels at any time (Shallo et al., 2020).

A growing number of empirical studies have shown that fuel switching is not unidirectional and that people may return to traditional fuels after switching to modern fuels (Masera et al., 2000; Heltberg, 2004), and households may only partially switch to modern fuels (Kowsari and Zerriffi, 2011). According to the model, many factors besides household income, such as age, gender, education, family size, occupation, access to electricity, dwelling characteristics, availability of kitchen, off-farm activities, distance to the fuel sources, etc., influence household fuel choice (Kowsari and Zerriffi, 2011; Van Der Kroon et al., 2013; Das et al., 2014; Mottaleb and Ali, 2017; Rahut et al., 2017; Danlami et al., 2018). The extent and dimension of how these factors influence household fuel choice behaviour vary from area to area and from one fuel source to another. This study hypothesizes that household fuel choice and use in the Semien Mountains and adjacent districts in northwest Ethiopia follows the fuel stacking model. Due to the availability of fuel stacking, it would be interesting to examine the choice of multiple energy sources for cooking.

3.3. Materials and Methods

3.3.1. Description of the Study Area

This study was conducted in the SMNP and adjacent *districts* in Northwest Ethiopia. It is situated at geographical coordinates between 13°29'21" to 13°29'40" N and 37°51'36" to 38°34'33" E, with an area of 241,093 ha (Debebe et al., 2023), comprising a population of about 378,929 (CSA, 2020). The SMNP is bordered by five administrative districts, including Adiarkay, Beyeda, Debark, Jan-amora, and Telemet. The study site is characterized by alternating dry and wet seasons with a mean annual rainfall of between 1,350 mm and 1,600 mm. The mean annual temperature ranges from -2℃ to 18℃ (Hurni and Ludi, 2000). The altitude of the study area ranges from 1,276 to 4,543 m above sea level and is rich in natural resources and endemic and endangered biodiversity (Asrat et al., 2012). Mixed farming, government employee, forest and wild products collection, wage labour, and small business are the major source of livelihood (EWCA, 2015). The primary daily energy supply is derived from traditional energy sources, namely fuelwood, dung, charcoal, and electricity. Because of the burgeoning population, the study area has undergone rapid settlement over the last decades.

3.3.2. Study Design, Data Sources, and Methods of Data Collection

The study employed a cross-sectional design consisting of both descriptive and analytic. It is a descriptive study to characterize household energy consumption patterns in detail. Because it involved testing a priori hypothesis about household energy choice, it is also an analytic study design. The data was gathered from both primary and secondary sources. A pre-tested semi-structured questionnaire was used to obtain the primary data. The questionnaire was prepared first in English, then translated into the local language, Amharic, and back to English to check consistency and understandability. After the questionnaire was assessed by experts, it was pretested on 20 households that did not include it in the actual survey. The pretesting helped to ensure questionnaire clarity, the relevance of questions, and the time taken for an interview. Accordingly, appropriate amendments were made to the questionnaire before beginning the actual household surveys. The questionnaire consisted of demographic and socioeconomic variables, housing characteristics, fuel acquisition, and utilization patterns: sources of energy, fuel availability, type of fuel used for cooking, and issues related to household energy use patterns. Respondents were interviewed at their homes by trained data collectors. Before data collection, data collectors and supervisors were

trained on data collection tools and how to obtain consent forms from respondents. The study considered household heads as the primary decision-maker concerning household energy use patterns. The authors follow ethical standards and principles throughout this study. The study households were contacted after getting an ethical approval letter from Addis Ababa University. Then, individual informed consent was obtained from potential participants, who were given the right to withdraw or refuse to answer specific questions at any time. The researcher, on the other hand, attempted to examine ethical issues throughout data collection to respect the right of participants.

3.3.3. Sampling Techniques

The study used a multi-stage sampling technique to select the study site, districts, kebeles, and sample households. Initially, the SMNP and adjacent districts were chosen purposively as a study site because (i) it is one of the most environmentally degraded areas in the ANRS, implying that a slight change in natural resources can have a far-reaching consequence on the livelihoods and associated ecosystem goods and services (ANRS, 2007) and (ii) it is an area where energy problems are intensive. In the second stage, out of five districts found in and around the Semien Mountains, Adiarkay and Debark districts[1] were purposively selected because they show significant variation concerning market access, infrastructure, proximity to forest resources, and availability of various energy sources (EWCA, 2015). In the third stage, six kebeles[2] were chosen randomly from the selected districts based on proximity to the source of fuel and market access, socioeconomic conditions, and availability of various energy sources. Finally, the households found in the selected kebeles during 2021 were identified and listed by the respective kebele administration. Then, the number of households selected from six kebeles was determined by dividing the sample size by the number of households in each kebele to get the representative sample households. Following that, 420 sample households were selected using a systematic random sampling technique, which was proportionally allocated to the household size of the six kebeles to ensure equal representation. Finally, the desired sample size was determined using Kothari (2004).

[1] District is the third level of the administrative division of Ethiopia after Zones.
[2] Kebele is the lowest administrative structure in Ethiopia.

3.3.4. Methods of Data Analyses

The data were entered into a statistical package for social science (SPSS V.20) and exported to STATA 14 for analysis. Descriptive statistics like frequency, percentage, graphs, mean, and standard deviations were employed to explain household socioeconomic, housing, and energy consumption patterns. A multivariate probit regression model was used to identify and analyze the factors that influence household cooking fuel choice decisions.

3.3.5. Econometric Model

This section describes our empirical framework-the discrete choice models employed to answer the research objective. Households in the study area depend on energy from various sources. When households are faced with energy options, they are more likely to choose a mix of fuels rather than rely on a single energy source. As a result, the choices to use different energy sources are correlated, and fuel choice decisions are inherently multivariate. Hence, we need to develop an empirical procedure to capture this interdependence. But, attempting univariate modeling would ignore useful information about interdependent and simultaneous fuel choice decisions (Rahut et al., 2017). For example, households may consider some combinations of fuel as complementary and others as competing. Failure to capture unobserved factors and inter-relationships among fuel choice decisions regarding various fuel choices will lead to biased and inefficient estimates (Tarekegn et al., 2017).

A shortcoming of most previous studies is that they do not consider the possible inter-relationships between the various energy sources. The empirical specification of choice decisions over the various sources of cooking energy can be modeled using either the multinomial logit (MNL) or multivariate probit (MVP) model. Previous studies have used the MNL model to deal with simultaneous binary decisions (Mekonnen and Köhlin, 2009; Rahut et al., 2014; Karimu, 2015; Alem et al., 2016). This model is appropriate when a household can choose only one outcome from a set of mutually exclusive alternatives. However, the problem with the MNL model is that it assumes the Independence of Irrelevant Alternative (s)[3] (IIA), which implies that the error terms of the choice equations are mutually exclusive and do not predict the joint interdependence of binary outcomes (Greene, 2003). However, the MVP model relaxes the property of the MNL. In the MVP model, the choices

[3] Independence of irrelevant alternatives states that the odds of choice do not depend on irrelevant alternatives.

among various energy sources are not mutually exclusive since households accessing cooking fuel from more than one source may be correlated (Rahut et al., 2017).

In this study, we used the MVP model, which simultaneously estimates the influence of the set of explanatory variables on each of the various fuel choices while allowing the unobserved/or unmeasured factors (error terms) to be freely correlated (Belderbos et al., 2004; Greene, 2003). Some of these energy sources can be used simultaneously as complements to other sources (positive correlation), while others can be used as substitutes (negative correlation) (Belderbos et al., 2004). As shown by Cappellari and Jenkins (2003), if a household *i* is faced with *m* different choices, then the multivariate probit model can be constructed as follows:

$$Y^*_{im} = X_{im}\,\beta'_m + \varepsilon_{im}\,, m = Y_1, Y_2\,,\ Y_3\,, Y_4\,, Y_5 \text{ and} \tag{1}$$

$$Y_{im} = \begin{cases} 1\ if\ y^*_{im} > 0 \\ 0\ otherwise \end{cases} \tag{2}$$

where m = $Y_1, Y_2\,,\ Y_3\,, Y_4\,, Y_5$ denotes the dependent variables, i.e., five cooking fuels available. In equation (1), the assumption is that a rational ith household has a latent variable, Y^*_{im}, which captures the unobserved preferences associated with the mth choice of cooking fuels. This latent variable is assumed to be a linear combination of observed characteristics (X_{im}), including socioeconomic, environmental, and institutional characteristics that affect the choice of mth cooking fuel, as well as unobserved characteristics captured by the stochastic error term ε_{im}. The vector of unknown coefficients/parameters (β'_m) are estimated using simulated maximum likelihood. Given the latent nature of Y^*_{im}, the estimations are based on observable binary discrete variables Y_{im}, which indicates whether or not a household undertook a particular cooking fuel.

If the choice of a particular cooking fuel is independent of whether or not a household uses another fuel (i.e., if the error terms, ε_{im}, are independent and identically distributed (IID) with a standard normal distribution), then equations (1) and (2) specify univariate probit models, where information on households' choice of one cooking fuel does not alter the prediction of the probability that they will choose another cooking fuel. However, if the choice of several cooking fuels is possible, a more realistic specification is to assume that the error terms in equation (1) jointly follow a multivariate normal (MVN) distribution, with

zero conditional mean and variance normalized to unity, where $\varepsilon_{im} \sim$ MVN (0, Σ) and the covariance matrix Σ is given by:

$$\Omega=\begin{bmatrix} 1 & \rho_{EC} & \rho_{EF} & \rho_{ED} & \rho_{ER} \\ \rho_{CE} & 1 & \rho_{CF} & \rho_{CD} & \rho_{CR} \\ \rho_{FE} & \rho_{FC} & 1 & \rho_{FD} & \rho_{FR} \\ \rho_{DE} & \rho_{DC} & \rho_{DF} & 1 & \rho_{DR} \\ \rho_{RE} & \rho_{RC} & \rho_{RF} & \rho_{RD} & 1 \end{bmatrix} \quad (3)$$

Of particular interest are the off-diagonal elements in the covariance matrix, ρ_{mj}, which represents the unobserved correlation between the stochastic component of the mth and jth type of cooking fuel choices. This assumption means that equation (2) gives the MVP model that jointly represents decisions to choose a particular cooking fuel. This specification with non-zero off-diagonal elements allows for correlation across the error terms of several latent equations, describing unobserved characteristics that affect the choice of alternative cooking fuels.

3.3.6. Description of Variables and Hypothesis

During the field survey, households reported five sources of cooking energy, including fuelwood, dung, crop residues, charcoal, and electricity. Some energy sources can be used as complements to others, while others may be used as substitutes. Households make five energy choice decisions, as each activity provides them with a certain threshold level of utility. Each choice of energy cannot be estimated separately as a single probit model because of the interdependence of error terms (Rahut et al., 2017). As shown in equation (1), the dependent variable, cooking energy choice, is based on five options. For each cooking energy source, a discrete binary variable takes the value 1 if it is chosen or 0 otherwise.

The choice of independent variables that were assumed to influence household energy choices was determined based on a review of theoretical literature and previous research findings (Van Der Kroon et al., 2013; Hou et al., 2017; Rahut et al., 2017; Danlami et al., 2018; Wassie et al., 2021). Table 12 illustrates the variables hypothesized to determine household cooking fuel choices. Before entering the predictors into the MVP model for further analysis, tests for the existence of multicollinearity problems were conducted using the Variance Inflation Factor (VIF) through STATA version 14 for continuous predictors and correlation matrix analysis for non-continuous explanatory variables. Accordingly, the results of multicollinearity tests showed that there were no multicollinearity problems.

Table 12: Description and measurement of variables and hypothesis.

Variables	Category	Measurement	Expected effect on cooking fuel choice				
			Elec.	Char.	FW	Du.	CR
Gender of household head	Dummy	1 if female, 0 male	+	+	+	-	-
Age of household head	Continuous	Age in years	+/-	+	-	-	-
Education of household head	Continuous	Years of schooling	+	+	-	-	-
Household size	Continuous	In number	-	-	+	+	+
Occupation of household head	Dummy	1 if farming, 0 salaried	-	-	+	+	+
Annual income	Continuous	In Ethiopian Birr	+	+	+/-	-	-
Participation in off-farm activity	Dummy	1 if participated, 0 otherwise	+	+	+	-	-
Type of House	Dummy	1 if corrugated, 0 thatched	+	+	+/-	-	-
Availability of separate kitchen	Dummy	1 if separate, 0 otherwise	+	+	+/-	+/-	-
Access to electricity	Dummy	1 if access, 0 otherwise	+	+	-	-	-
Distance to market	Continuous	Walking distance in minutes	-	-	+	+	+
Distance to the forest	Continuous	Walking distance in minutes	-	+	+	-	-

Elec. - Electricity; Char. - Charcoal, FW - Fuelwood; Dun. - Dung; CR - Crop residue

3.4 Results and Discussion

3.4.1. Household Socio-economic Characteristics

A total of 420 households were sampled for the survey, but only 403 were analyzed, resulting in a 96% response rate (Table 13). The results revealed that males headed 75% of the sampled households. The mean age of the household head was 45.2 years, with 24 and 71 being the minimum and maximum, respectively, and household heads' average years of schooling were 4.6 years. The average household size was about 5.5 persons, which is larger than the national average (4.6) (CSA, 2016) and regional average (4.6) (CSA, 2013a). The average yearly income of the sampled households was estimated at Birr 18,123. In addition, 65% of the households in the sample engaged in off-farm activities.

Regarding occupational status, 75% of household heads work in agriculture. Descriptive statistics show that 73% of sampled households live in a modern house. Additionally, 38% and 63% lacked separate kitchen facilities and access to electricity, respectively. Moreover, about 27% of the 403 households were unaware of the health effects of biomass fuel burning. Furthermore, on average, households travel 130 minutes and 69 minutes to the nearby market

and forest source, respectively, which probably determines the type of fuel used by households.

Table 13: Summary statistics of variables used in the study.

Categorical Variables	**Responses**	**Frequency**	**Percentage**
Gender of the household head	Female	102	25
	Male	301	75
Occupational of the household head	Farming	301	75
	Paid employment	102	25
Access to electricity	Yes	149	37
	No	254	63
Type of house	Modern	296	73
	Traditional	107	27
Availability of separate kitchen	Yes	251	62
	No	152	38
Awareness about the harmful effect of biomass energy sources	Yes	296	73
	No	107	27
Participation in off-farm activities	Yes	262	65
	No	141	35
Continuous Variables	**Observations**	**Mean**	**Std. Dev.**
Age of the household head (Years)	403	45.2	11.4
Educational level (Year of schooling)	403	4.6	3.4
Household size (Number)	403	5.5	1.8
Annual Income (Birr)	403	18123	9965
Distance to the nearest market (Minutes)	403	130	88
Time spent to collect fuelwood (Minutes)	403	168	89
Distance to the forest (Minutes)	403	69	37

Source: Field Survey (2021)

3.4.2. Patterns and Sources of Household Energy Use

The results revealed that 87% of the households predominantly used fuelwood, followed by cattle dung (82%) and crop residue (34%). In contrast, only 33% and 17% of the sampled households used charcoal and electricity as the main baking and cooking energy sources (Table 14). The prevalence of poverty influences the increased use of fuelwood and dung; thus, they cannot afford to invest in modern energy sources, such as electricity.

Table 14: Proportion of households using different sources of energy for domestic use.

Type of fuel used *	Frequency	Percentage (%)
Electricity	68	16.9
Charcoal	131	32.5
Fuelwood	352	87.3
Dung	330	81.9
Crop residue	136	33.8

Source: Field survey (2021) * multiple responses

Since biomass fuel, particularly fuelwood, was predominantly used by sampled households in the study area, it may imply easy availability and affordability of biomass (Table 15). There are various sources from which a household can obtain fuelwood. Among the fuelwood users, 33% collected from their farm, 54% from off-farm (community and state forests), and 13% reported purchasing from the market. According to the study discussants, rapid land use and forest cover changes have reduced biomass supply. This has strained state and community forests and resulted in fuelwood scarcity in the area.

Table 15: The proportion of Households by fuelwood collection sources

Fuelwood collection sources	Frequency	Percentage (%)
On-farm	134	33.2
State and community forest	218	54.1
Purchasing	51	12.7

Source: Field survey (2021)

Owing to the government ban on fuelwood collection from state forests in the study area, the percentage of households using cattle dung, crop residue, and communal land has continued to rise. Dried dung was available for free since livestock rearing was common. The results revealed that owned livestock was a significant source of cattle dung (55%), and 45% was collected from other farms (Figure 10b). Similarly, crop residues of wheat, barley, and sorghum were commonly used as fuel by the sampled households. Similarly, about 80% of the households that use crop residues depend on their farm, and 20% are collected from other farms (Figure 10a).

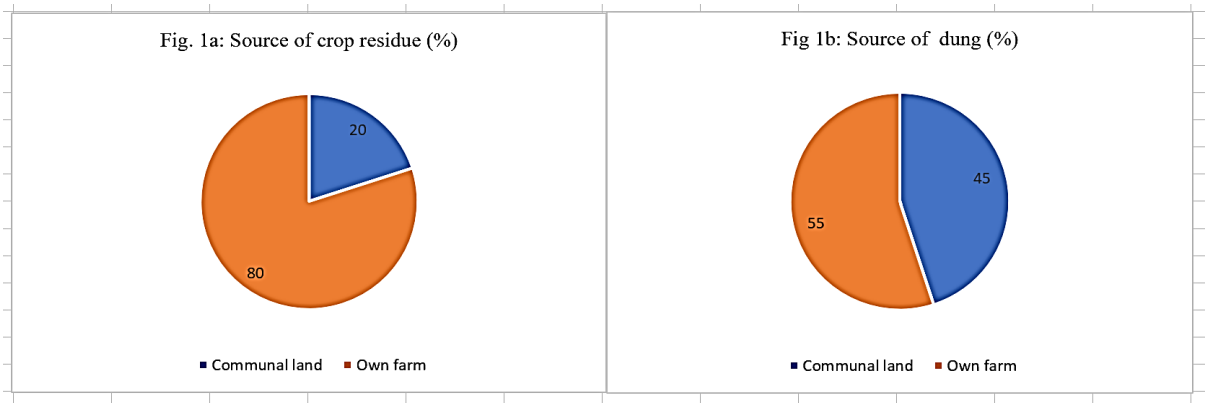

Figure 10: (a) and 10 (b) Source of crop residue and dung.

Source: Field survey (2021)

Moreover, 77% of the sampled households perceived a decrease in fuelwood availability over time (Fig. 11a). According to key informants, forest loss is primarily caused by an increase in human population. The decline in fuelwood availability indicates the over-exploitation of forests and the increased time spent by fuelwood collectors. The results revealed that fuelwood collectors are required to walk (round trip) for a minimum of 60 minutes and a maximum of 360 minutes to collect headloads of fuelwood, with an average of about 168 minutes (Table 13). On the other hand, both male and female members of households are involved in collecting fuelwood. The results demonstrated that women are the most likely (40%) to collect fuelwood, followed by girls (31%) and boys (27%) (Fig.11b).

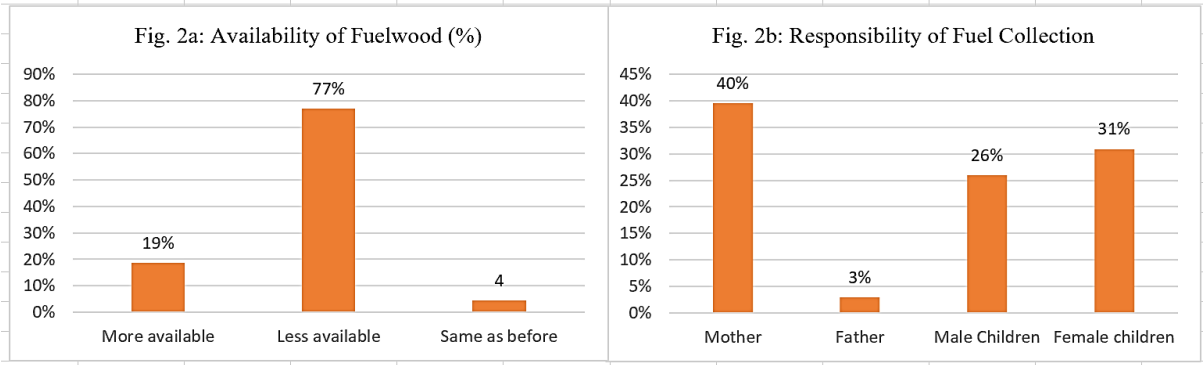

Figure 11 (a) & (b): Availability of fuelwood & responsibility of collection.

Source: Field survey (2021)

3.4.3. Econometric Analyses: Determinants of Household Fuel Choices

In this study, 12 predictors were hypothesized to influence household cooking fuel choice. The results showed the effect of each predictor on each dependent variable category, suggesting that one predictor may have a significant and positive or negative effect on one or more or none of the variables. The estimated correlation coefficients were statistically significant in six of the ten pair cases, with two coefficients having positive and the remaining four having negative signs (Table 16). The result supports the hypothesis that error terms of multiple fuel choice decisions are correlated. As a result, cooking fuel choices within a single household were mutually inclusive, allowing us to apply the MVP model to estimate household fuel choices. The likelihood ratio test [χ^2 (10) = 61.74, Prob > χ^2 = 0.000] of the null hypothesis that the covariance of the error terms across equations is not correlated is also rejected. Crop residue and fuelwood, as well as crop residue and dung, were significantly and positively associated, implying that these fuels are primarily considered complements by households. On the other hand, charcoal and electricity, as well as fuelwood and electricity, were significantly and negatively associated, suggesting these energy sources were used as substitutes for households (Table 16).

Table 16: Correlation coefficients between energy sources used by households.

Parameter	Correlation Coefficient	Standard error	Z-value
Charcoal and Electricity	-0.2534	0.1505	1.684*
Fuelwood and Electricity	-0.2811	0.1592	-1.770*
Dung and Electricity	0.1157	0.1467	0.790
Crop residue and Electricity	0.1401	0.1507	0.930
Fuelwood and Charcoal	-0.2898	0.1017	-2.850***
Dung and Charcoal	-0.0888	0.1284	-0.692
Crop residue and Charcoal	-0.0440	0.1120	-0.339
Dung and Fuelwood	-0.7600	0.1520	-4.990*
Crop residue and Fuelwood	0.2720	0.1030	2.640***
Crop residue and Dung	0.2585	0.1131	2.280**

Likelihood ratio test of rho21=rho31=rho41=rho51=rho32=rho=42=rho43=rho=53=rho54=0; χ^2 (10) = 60.05, Prob > χ^2= 0.*0000*; *, **, and *** refer to significant at 10%, 5%, and 1% level, respectively.

The MVP model fits the data reasonably well as the Wald test [χ^2 (60) = 294.94; Prob > χ^2=0.0000] of the null hypothesis that all regression coefficients in each equation were jointly equal to zero was rejected, suggesting that the variables included in the model explain significant portions of the variations in the dependent variables (Table 17). As evident from the MVP regression results, the estimated coefficient of the age of the household head was

negative and statistically significant for the choice of electricity ($P < 0.01$) but positive and significant for the choice of dung ($P < 0.1$). This suggests that the probability of choosing dung increases as the age of the household head increases. This might be because cattle dung is readily available. Besides, older household heads are known to resist change, often adhere to social norms, and thus rely on biomass. This corresponds to the findings of Mekonnen and Köhlin (2009), Baiyegunhi and Hassan (2014), Rahut et al. (2016), Giri and Goswami (2018), Paudel et al. (2018), Rahut et al. (2020), and Mottaleb (2021). But, the probability of choosing electricity decreases as the age of the household head increases. This might be associated with the perception that older people feel that electricity is not safe to use and not readily available and affordable, like biomass fuels. This finding is in accord with Abdul-Wakeel Karakara and Dasmani's (2019) finding. However, it contradicts the findings of Gebreegziabher et al. (2012), Guta (2012), Rahut et al. (2017), and Mottaleb and Rahut (2021), who found a positive relationship between age and the choice of modern energy sources. This is because of the household heads' life cycle effect, i.e. the higher a household head moves up in their life cycle, the wealthier they become and the more likely to invest in modern fuels (Van Der Kroon et al., 2013). Also, Rahut et al. (2020) concluded that the elderly need more convenient fuel sources because they are not as strong as those who have to travel a long distance to collect biomass fuels.

Besides, the estimated coefficient of female-headed households was positive and significant for the choice of electricity ($P < 0.05$) but negative and significant for the choice of fuelwood ($P < 0.01$) and crop residue ($P < 0.1$). This implies that the probability of choosing electricity is more likely when the household is female-headed. This may be attributed to the fact that females are often responsible for cooking and are more concerned about the hazardous health effects of biomass fuels and are, thus, less inclined to use biomass fuels. This finding is consistent with the findings of Rahut et al. (2014), Behera et al. (2015), Mensah and Adu (2015), and Mottaleb (2021). But, it contradicts the findings of Mekonnen and Köhlin (2009) and Abdul-Wakeel Karakara and Dasmani (2019), who found that female-headed households may not have the economic strength to use electricity and are more likely to use biomass fuels.

Again, the result shows that the coefficient of household size is negative and statistically significant for the choice of electricity ($P < 0.1$) but positive and significant for the choice of fuelwood ($P < 0.1$) and crop residue ($P < 0.1$). Increasing family sizes implies abundant labor for fuel collection, limiting the need to move to modern fuels. Besides, a large household

requires more energy and thus chooses biomass energy sources. This finding is concurrent with past studies conducted in Ethiopia (Guta, 2012) and other developing countries Giri and Goswami (2018); Muller and Yan (2018); Paudel et al. (2018). However, this finding contradicts the findings of Pandey and Chaubal (2011) and Twumasi et al. (2020), who reported that a negative association exists between household size and the choice of electricity.

Table 17: Results of Multivariate probit estimation of household cooking fuel choice.

Explanatory Variables	Dependent Variables (Choice of Fuel)				
	Electricity	Charcoal	Fuelwood	Dung	Crop residue
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Age of the household head	-0.167	-0.008	0.003	0.019	0.003
	(0.087)***	(0.008)	(0.009)	(0.011)*	(0.008)
Gender of household head	4.779	0.247	-0.578	-0.286	-0.312
	(2.314)**	(0.177)	(0.197)***	(0.226)	(0.192)*
Household size	-0.947	0.102	0.080	0.031	0.217
	(0.526)*	(0.042)***	(0.048)*	(0.055)	(0.045)***
Education of the household head	0.068	0.007	-0.018	-0.061	-0.057
	(0.026)***	(0.024)	(0.029)	(0.031)**	(0.031)***
Occupation of the household head	-1.969	-0.579	-0.202	1.137	-0.270
	(1.338)***	(0.215)***	(0.273)	(0.267)***	(0.235)
Log_household income	5.693	0.472	-0.582	-0.057	-0.139
	(3.138)*	(0.242)**	(0.274)**	(0.327)	(0.067)***
Distance to the market	-0.075	0.001	0.002	0.003	-0.002
	(0.037)**	(0.001)	(0.001)*	(0.001)*	(0.001)*
Type of house	4.063	0.169	0.356	-0.880	-0.913
	(6.580)	(0.219)**	(0.246)	(0.338)***	(0.214)***
Participation in Off-farm	2.380	0.003	-0.184	-0.367	-0.191
	(1.262)*	(0.163)	(0.194)	(0.229)*	(0.155)
Access to electricity	6.744	1.100	0.157	-1.108	-1.384
	(3.427)**	(0.207)***	(0.247)	(0.278)***	(0.226)***
Availability of kitchen	2.314	-0.111	-0.061	-0.526	-0.376
	(0.861)***	(0.218)	(0.244)	(0.333)*	(0.204)*
Distance to forest	-0.040	0.002	0.051	-0.005	-0.004
	(0.079)	(0.002)	(0.030)*	(0.002)**	(0.002)**
Number of obs =	403				
Log likelihood =	-605.49				
Wald $\chi^2(60)$ =	294.94				
Prob > chi2 =	0.0000				

Values in the parenthesis are standard errors.

*, **, *** refer to significant at 10%, 5%, and 1% levels, respectively; Source: Field survey (2021)

Interestingly, education is an important policy tool to raise households' awareness about the benefits of modern energy sources and the risk of biomass fuels. Our result indicates that the estimated coefficient of the household head's years of schooling showed a positive and

statistically significant effect on the choice of electricity ($P < 0.01$), but it was negative and significant with the choice of dung ($P < 0.05$) and crop residue ($P < 0.01$). This implies that as the household head's years of schooling increase, so does the likelihood of using electricity. This was most likely explained by the increasing opportunity costs of fuel collection time at higher education levels and the increased awareness of the adverse health and environmental effects of using biomass fuels. This finding is consistent with results from past studies conducted in Ethiopia by Mekonnen and Köhlin (2009), Gebreegziabher et al. (2012), and Guta (2012) and other developing countries (Lay et al., 2013; Rahut et al., 2014; Behera et al., 2015; Imran et al., 2019; Mottaleb and Rahut, 2021). However, this finding contradicts the finding of Sehjpal et al. (2014), who found that education does not directly impact household sources of energy choice. The argument is that education may indirectly influence the use of modern energy if only it leads to employment, which, in turn, may increase income (Hou et al., 2017). But, whether education influences the use of modern energy directly or indirectly, the consensus is that education plays a vital role in determining household energy choices.

In addition, the type of occupation of a household head may affect the cooking fuel choice. The results revealed that the effect of household heads engaged in farming is negative and significant for the choice of electricity ($P < 0.01$) and charcoal ($P < 0.01$) but positive and significant for the choice of dung ($P < 0.01$). It implies that household heads involved in farming are more likely to use biomass than electricity. However, household heads employed in the public sector are more likely to choose electricity or charcoal. This might be because the opportunity cost of collecting biomass fuels is high for public sector employees, corroborating past research findings (Pandey and Chaubal, 2011; Rahut et al., 2016).

Moreover, household income is assumed to be the main driver when choosing the type of energy. Although income plays an important role in cooking fuel choice, many still dispute it. According to Akpalu et al. (2011), income increase has not shifted households to modern fuel, while Kowsari and Zerriffi (2011) explained households use a mix of energy sources rather than one particular source of energy. The results revealed that the estimated coefficient of income was positive and significant for the choice of electricity ($P < 0.1$) and charcoal ($P < 0.05$), but it was negative and significant for the choice of fuelwood ($p < 0.05$) and crop residue ($P < 0.01$). This suggests that higher-income households are more likely to invest in and use electricity. One possible explanation is that household purchasing power improves

as income increases, making electricity more affordable. This finding concurs with those of Behera et al. (2015), Mensah and Adu (2015), Alem et al. (2016), and Imran et al. (2019).

Another predictor variable influencing household energy choice was the distance from the market. The coefficient of the distance to the market is negative and significantly associated with the household choice of electricity ($P < 0.01$) and positive and significantly associated with fuelwood ($P < 0.1$) and dung ($P < 0.1$). This suggests that households living further away from the market are more likely to use biomass and less likely to use electricity. This is because modern fuels like electricity are probably more likely to be available around the main market center. The findings of this study are consistent with those of previous studies conducted in developing countries by Van Der Kroon et al. (2013), Behera et al. (2015), Rahut et al. (2017), and Imran et al. (2019).

Housing type can be viewed as an indicator of household living conditions, affecting household energy choice. A variety of housing attributes can be considered in the literature. In this study, the material used to construct the roof of the house are used to classify it into two categories: modern (corrugated roofs) and traditional (thatched roofs). In the case of a household living in a modern house, the estimated coefficient of charcoal is positive and statistically significant ($p < 0.05$), but it is negative and statistically significant for dung ($P < 0.01$) and crop residue ($P < 0.01$). This implies that households living in modern houses have a higher propensity to choose and use charcoal, which is in line with the finding of Baiyegunhi and Hassan (2014).

Another predictor variable that affects household energy choice is household access to electricity. Access to electricity is seen as an essential input for micro and small enterprises, which are the main contributors to job creation and improving the livelihoods of society. The results showed that the coefficient for access to electricity was positive and statistically significant for the choice of electricity ($P < 0.05$) and charcoal ($P < 0.01$), but it was negative and significant for the choice of dung ($P < 0.01$) and crop residue ($P < 0.01$). This implies that households with access to electricity are more likely to use electricity relative to households without access to electricity. This is most likely because using electricity is linked to an improvement in the standard of living and availability. This finding is in line with results reported from studies conducted in Ethiopia (Daniel, 2020; Wassie et al., 2021) and other developing countries (Karimu, 2015; Rahut et al., 2016; Lokonon, 2020), which found a positive association between access to electricity and electricity use. However, this

finding is in contrast with the finding of Trac (2011), who found that electricity availability within a household does not necessarily mean the use of modern energy sources for all energy consumption. For example, some meals may still be cooked using biomass fuels because of social norms, which agrees with the fuel stacking theory.

Participation in off-farm activities was also a factor that influenced the choice of source of energy. The estimated coefficient for a household participating in off-farm activities was positive and statistically significant for the choice of electricity ($P < 0.1$). In contrast, it was negative and significant for the use of dung ($P < 0.1$). This indicates that when a household head is engaged in off-farm income, the probability of choosing electricity is enhanced since income from off-farm activities helps the household to earn supplementary income to diversify and invest in various modern energy alternatives. This finding supports the findings of Ma et al. (2019) and Lin and Zhao (2021), who indicated a positive association between off-farm income and the probability of households using electricity.

Moreover, the availability of a separate kitchen was identified as an important factor influencing household sources of energy choice. The estimated coefficient for the availability of a separate kitchen is a positive and statistically significant effect on the choice of charcoal ($P < 0.01$). At the same time, it is negative and significant for the choice of dung ($P < 0.05$) and crop residue ($P < 0.01$). This implies that households with no separate kitchens are more likely to choose biomass for cooking. A possible explanation is that households with separate kitchens are more aware of the harmful effects of IAP caused by burning biomass fuels. This finding corroborates the findings of Pundo and Fraser (2006), Paudel et al. (2018), and Daniel (2020).

Furthermore, distance from the forest influences a household's fuel choice decisions. The results showed that the coefficient of the distance to the forest had a negative and significant effect on the choice of dung ($P < 0.05$) and crop residue ($P < 0.05$), but it was a positive and significant effect on the choice of fuelwood ($P < 0.1$). This suggests that households are less likely to switch to modern fuels when they are closer to the forest source. The possible reason might be the opportunity cost of collecting fuelwood is lower, which is in line with the findings of Joshi & Bohara (2017).

3.5. Conclusions and Policy Implications

This study examined household energy utilization patterns and factors affecting cooking fuel choice in the SMNP and adjacent districts using data from 420 randomly selected households. Since this study was cross-sectional and we could not examine how the variables changed over time, the findings should be treated with caution. Nevertheless, results indicate that households' energy utilization pattern is skewed towards biomass fuels, particularly fuelwood. The results also showed that fuelwood is not inferior, as opposed to the energy-ladder hypothesis, and households continue to rely mainly on these fuels for cooking. However, although fuelwood is a renewable fuel source, over-extraction can lead to deforestation and environmental degradation and thus can significantly negatively impact sustainable development. Besides, our findings revealed that households choose multiple fuels for domestic chores for various reasons, including that entire reliance on single energy may be subject to price fluctuations and unreliable supply. Thus, households tend to follow a multiple fuel use strategy as their income, education, and settlement patterns improve. Empirical results of the MVP model further reveal that a mix of factors, including age, gender, household size, education, income, access to electricity, off-farm activities, distance to forest, access to market, and type of house considerably govern a household's choice of cooking fuel and the extent of dependency on it.

The study has substantial policy implications that should be considered in policy design. First, this study's findings reveal that education has positive returns on people's energy choice behavior. As a result, raising public awareness of the adverse effects of an overreliance on biomass on both human health and the environment is vital. These social norms, as a result, encourage the use of modern fuels. Besides, a slow transition to electricity is evident because only about 17% of grid-connected households use electricity for domestic use. Therefore, the study strongly recommends investing in overall livelihood improvement programs, human capital, and improving the provision of infrastructure to encourage the use of electricity for cooking. Finally, switching to a modern energy source will take time because biomass is still the most common energy source for domestic chores. Thus, policymakers should encourage households to use fuel-efficient cooking stoves to increase biomass cooking efficiency.

CHAPTER FOUR: PERFORMANCE OF IMPROVED BIOMASS COOKING STOVES AND DETERMINANTS OF ADOPTION IN NORTHWEST ETHIOPIA: IMPLICATIONS FOR ENERGY AND TIME SAVING

ABSTRACT

Cooking with biomass and traditional stoves causes substantial social, environmental and health risks. Improved cooking stoves have been launched as a technological option in many developing countries, including Ethiopia, to reduce these adverse effects. The major attempt of this study is to examine the effectiveness of improved cooking stoves on fuel and time-saving. Besides, the study identifies factors affecting the use of Mirt stove technology in Northwest Ethiopia. A kitchen performance test was applied based on three days of repeated fuelwood measurement from randomly selected 15 Mirt stove users and 20 three-stone stove user households. In addition, 420 households were surveyed to identify the factors affecting Mirt stove adoption. The data were analyzed using descriptive statistics and a binary logistic regression model. An independent t-test was also employed to analyze the kitchen performance test. The results of the kitchen performance test reveal that Mirt stoves saved household fuelwood consumption by 777 kg (40.5%) per household per year. In addition, Mirt stoves reduce the time needed to bake injera compared to three-stone stoves by 23.5 minutes (28%), equivalent to an annual per capita time-saving of about 56.4 hours. The survey results indicated that 73% and 27% of the sampled households used traditional and Mirt-improved stoves, respectively. Further, estimates of the empirical results highlighted that household age, sex, education, family size, type of housing, availability of kitchens, access to credit, and access to information significantly influence Mirt stove adoption. On the other hand, distance from the stove market and fuel sources have a negative influence on Mirt stove adoption. The findings suggest that sample households exhibited interest on Mirt stoves. However, widespread adoption is unlikely owing to the distance to the stove market, lack of stove producers, and lack of awareness about the benefit and availability of forest resources. Thus, the study confirms that Mirt stoves, if well adapted to the local cooking needs, can make a significant contribution to the conservation of forests and the reduction of carbon emissions from deforestation and forest degradation.

Keywords: Adoption, Cookstove, Fuel-Saving, Kitchen Performance Test, *Mirt* stove, Three-stone stove

4.1. Introduction

Energy plays a crucial role in the socio-economic and sustainable development efforts of nations (Jan et al., 2017). Access to clean, affordable energy services is vital for sustainable development (Sopian et al., 2011). Sustainable development goal necessitates a sustainable supply of energy resources that are affordable, readily available, and suitable for all necessary tasks without causing any adverse effect on the environment and society (Rosenthal et al., 2018). Nevertheless, many people across the world still lack access to clean, modern, reliable, and sustainable energy sources (Baiyegunhi & Hassan, 2014; Mottaleb et al., 2017). Inadequate energy supply is expected to severely affect developing countries, particularly Sub-Saharan Africa (SSA) (Behera et al., 2015). In SSA, over 780 million people (> 80%) rely on biomass fuels and use open-fire and inefficient stoves to fulfil their daily cooking needs (IEA, 2017). Cooking using traditional methods consumes significant amounts of biomass fuels due to low burning efficiency (Jan et al., 2017; Suresh et al., 2016). Traditional and inefficient cooking practices can be harmful to the environment, releasing harmful pollutants, such as carbon monoxide, fine particulates, and various dangerous polyaromatic hydrocarbons (Kees & Feldmann, 2011). Many of these pollutants have harmful effects on human health (Kees & Feldmann, 2011; Adrianzén, 2013), and they also cause severe environmental damage, particularly linked to environmental degradation and greenhouse gas (GHG) emissions (Karanja & Gasparatos, 2019), which contribute to global climate change (Suresh et al., 2016). According to WHO (2018), around 3.2 million people die annually owing to exposure to indoor air pollution (IAP) from biomass fuel uses.

One way of reducing the various harms associated with the traditional cooking stove is by popularizing and adopting improved cookstoves (ICSs) (Jeuland et al., 2020; Kshirsagar & Kalamkar, 2014). ICS was first introduced in India in 1940 (Kumar et al., 2013) when the world became increasingly interested in environmental concerns and the need for energy conservation measures (Arnold et al., 2006). Since then, many ICSs programs have been introduced in developing countries as technological alternatives to mitigate multifaceted problems related to traditional energy usage (Tania Urmee and Samuel Gyamfi, 2014). ICS has the potential to save fuel, minimize the time spent on fuel collection, and reduce cooking times (Brooks et al., 2016; Suresh et al., 2016; Onyeneke et al., 2017). More recently, efforts have been made to reduce air pollution and the safety impacts of biomass fuel use through various health improvement programs (Ruiz-Mercado et al., 2011). These effects can, in turn, improve productivity, thereby increasing household income (Lewis & Pattanayak,

2012; Mehetre et al., 2017); can reduce IAP and GHG emissions (Pine et al., 2011; Mamuye et al., 2018; Negash et al., 2021; Manaye et al., 2022), reduce the pressure of local forest clearance (Jeuland & Pattanayak, 2012; Mehetre et al., 2017; Beyene et al., 2022), and mitigate local climate change (Suresh et al., 2016). The adoption of ICS has the potential to contribute to meeting at least five of the Sustainable Development Goals (SDGs), particularly SDG-7 (Rosenthal et al., 2018).

Despite the many social, economic, health, and environmental benefits of ICS, their adoption remains low in many developing countries (Mehetre et al., 2017). Empirical study suggests that the adoption of ICS varies at the household and community levels (Pine et al., 2011). For example, some household characteristics, like income, occupation, educational status, and type of house, determine the initial acceptance of stoves (Troncoso et al., 2013). In addition, stove adoption can be affected by various factors such as low trust in technology (Pokharel, 2003), the mismatch between cookstove characteristics and local needs (Kapfudzaruwa et al., 2017), lack of knowledge about the benefits of ICSs (El Tayeb Muneer & Mukhtar Mohamed, 2003; Mobarak et al., 2012), and low consumer awareness (Mehetre et al., 2017).

Although laboratory tests suggest that ICS generally perform better than open fires, their performance in actual field conditions can vary significantly from the results observed in controlled cooking tests (Adrianzén, 2013). However, empirical evidence on the performance of ICS is limited and mixed. For instance, a study conducted in Kenya concluded that using Rocket mud stoves resulted in a daily fuel saving of 1.6 kg compared to three-stone stoves (Ochieng et al., 2013). Suresh et al. (2016) report that the use of forced cookstoves in India has resulted in a significant reduction of indoor $PM_{2.5}$ and CO concentrations. Specifically, there was a 21-57% reduction of $PM_{2.5}$ and 30-74% for CO compared to the traditional stove. According to the research conducted by Brooks et al. (2016), the adoption of ICS in two Indian states resulted in a daily reduction of about 4.5 kg of biomass fuels, 160 minutes less time spent on cooking using traditional stoves, and 105 minutes less time spent on collecting biomass fuels. Unlike other studies, the improved Esperanza stove consumed 86% more fuelwood compared to the three-stone stove in Southern Malawi (Chagunda et al., 2017). A study conducted in the highlands of Guatemala found that improved stoves (Plancha) did not offer any fuel-saving benefits (Granderson et al., 2009). Similarly, Nepal et al. (2011) found that households with ICS in Nepal consumed

more fuelwood than those with mud stoves. These disparate findings necessitate further research.

In Ethiopia, empirical evidence regarding the performance of improved cooking stoves in the real kitchen environment is very limited. A study in the Southern region, for instance, showed that the adoption of a *Mirt* stove ('*Mirt'* means 'best' in Amharic used for baking injera and cooking food while baking without the use of additional fuel) resulted in a 31% reduction in fuelwood consumption compared to the traditional three-stone stove (Yayeh et al., 2021). Another study conducted in Kafa, Southern Ethiopia, revealed that using a *Mirt* stove for injera preparation saves up to 40% of fuelwood compared to the traditional three-stone stove (Dresen et al., 2014). Similarly, a study by Gebreegziabher et al. (2018) in Ethiopia with a controlled cooking test shows that *Mirt* stoves offer a 22% - 31% reduction in fuel usage compared to a traditional three-stone tripod, with little or no increase in cooking time. Besides, Wassie & Adaramola (2021) concluded that using ICSs reduces household fuelwood consumption on average by 1.72 - 2.08 tons per household per year. Although the social, economic, and environmental benefits of improved stoves seem to be rather clear, the adoption rate is not as fast as expected and anticipated in Ethiopia. None of these studies applied the kitchen performance test in a real kitchen.

Ethiopia, like numerous other SSA countries, heavily depends on biomass fuels, which make up approximately 88% of its total energy supply (Tiruye et al., 2021). The heavy reliance on biomass fuels and the inefficient utilization of energy from traditional open-fire stoves have contributed to forest degradation in many parts of the country (Gebreegziabher et al., 2012; Beyene & Koch, 2013). In addition, the utilization of biomass fuels in an unsustainable manner has led to a rise in CO_2 emissions from 5.1 million tons in 2005 to 6.5 million tons in 2010 (Mondal et al., 2018; Manaye et al., 2022). In Ethiopia, it is common for people to prepare *injera* (a sour fermented pancake-like flatbread with a slightly spongy texture, traditionally made of teff flour in Ethiopia and Eritrea) in open-fire stoves (*see* Fig.1). However, these stoves have low thermal and fuel efficiency (13-15%) and consume over 60% of household energy (Gebreegziabher et al., 2017; Beyene et al., 2022). This directly impacts the sustainability of biomass utilization, biodiversity conservation, and the country's climate resilience (Wassie & Adaramola, 2021).

In the 1990s, the Government of Ethiopia, in partnership with the German Development Agency (GIZ) and other NGOs, introduced and popularized a type of improved stove called

a *Mirt* stove (Megen Power, 2008). The goal was to improve energy efficiency and mitigate the harmful effects of traditional stoves on people's health, the economy, and the environment (Mamuye et al., 2018). Moreover, Ethiopia has targeted clean and renewable energy to realize sustainable development and a climate-resilient green economy (Desta et al., 2020). In addition, Ethiopia's Climate Resilient Green Economy (CRGE) strategy lists ICSs as one way to enhance energy efficiency in the off-grid renewable energy system (FDRE, 2011). Accordingly, the Government distributed 9.4 million ICS of various types between 2010 and 2015. Furthermore, between 2016 and 2020, the Government, through Ethiopia's national improved cookstoves program (NICSP), aims to distribute over 11 million ICS, most of which are designed for baking *injera* efficiently (Gebreegziabher et al., 2018).

Figure 12: A picture of injera.

However, recent reports have shown that only 10% of Ethiopian households have adopted ICS (MEFCC, 2018), which is lower than global and SSA adoption rates (IEA, 2017). There has been little study on factors influencing the adoption of ICSs like *Mirt* stoves. Gizachew & Tolera (2018) claim that various contextual factors influence people's decisions to adopt ICS. The debate on the drivers of low adoption of ICS is still open in the literature. A recent systematic review of the existing literature in Ethiopia identified some barriers to low adoption (Adane et al., 2020). These are household wealth, lack of coordination, insufficient market development, lack of knowledge about the environmental and health benefits, cultural factors, stove design, and diffusion programs (Woubishet, 2009; Beyene & Koch, 2013; Eshetu, 2014; Kooser, 2014; Beyene et al., 2015; Gebreegziabher et al., 2018; Wassie & Adaramola, 2021; Yayeh et al., 2021).

On the other hand, inadequate field research has been conducted on the baking time duration and fuel-saving performance of *Mirt* stoves in Ethiopia. Assessments of the improved stoves' effectiveness in reducing fuel consumption have primarily been based on Water Boiling Tests (WBT) and Controlled Cooking Tests (CCT) (Dresen et al., 2014; Beyene et al., 2015; Gebreegziabher et al., 2018; Yayeh et al., 2021). It's worth noting that the techniques may not provide accurate predictions for the outcomes of ICSs in an unpredictable environment where multiple stoves and fuel types are used simultaneously (Chagunda et al., 2017; Manaye et al., 2022). The Kitchen Performance Test (KPT) is a common method to assess the effectiveness of improved stoves in reducing fuel consumption. This test is conducted in the actual kitchens of households as a field-based assessment (Bailis et al., 2007). However, empirical evidence on the performance of *Mirt* stoves on fuel and cooking time saving is generally lacking in environmentally susceptible areas of the Semien Mountains and adjacent districts of Northwest Ethiopia. Thus, the objective of this study was to: (a) determine the factors influencing the adoption of *Mirt* stoves and (b) assess the performance of *Mirt*-improved stoves in fuel and baking time-saving compared to three-stone stoves in the actual kitchens of households using the KPT method.

To this end, the contribution of this study is twofold. First, although fuelwood scarcity has reached an alarming rate in and around the Semien Mountains and adjacent districts of Northwest Ethiopia, field-based analysis of traditional stoves and *Mirt*-improved stoves about fuelwood and time consumption is unavailable. In order to contribute to the adoption and knowledge-based uptake of *Mirt*-improved stoves, this study seeks to provide evidence-based results on the performance of *Mirt* stoves and traditional stoves through kitchen performance tests. Second, a thorough understanding of the factors that determine the adoption of *Mirt* stove technology may serve as input to formulating and implementing informed policies, accelerating the transition of households to clean energy. Therefore, policies aimed at reducing deforestation and improving the livelihoods of the poor should begin with promoting fuel-efficient stoves.

4.2. Materials and Methods

4.2.1. Study Area

The study was conducted in two districts of North Gondar Zone, Amhara National Regional State, Northwestern Ethiopia. The North Gondar Zone is characterized by four agroecological settings, known locally as Wurch, Dega, Woina-Dega, and Kolla. It

encompasses an area of 241,093 ha with altitudes ranging from 1,276 to 4,540 m (Debebe et al., 2023). The study area is located in one of the wettest and coldest regions of the country, with a mean annual rainfall of between 1,350 and 1,550 mm falling in a single rainy season, whereby the highest precipitation is between June and September (Hurni & Ludi, 2000). Mean daily temperatures range from a minimum of 2.5°C to 4°C to a maximum of 11°C to 18°C (Asrat et al., 2012). The total population was estimated to be 378,929 in 2016 (CSA, 2020), with an average household size of 6.01 (AWF, 2019), living at altitudes between 1,500 and 3,800 m (ANRS, 2007). The study area is significant for biodiversity conservation since it is a habitat for several endangered endemic species, including the iconic and severely endangered Walia ibex (*Capra walie*) and Ethiopian wolf (*Canis simensis*) (Asrat et al., 2012). Like in other parts of Ethiopia, biomass constituting fuelwood is the primary source of energy for local communities. More than 90% of the total energy for household cooking and baking is derived from biomass fuels, mainly about 87% from fuelwood. Further, electricity and kerosene are used as energy sources in the study areas (Debebe et al., 2023).

4.2.2. Data Sources and Methods of Data Collection

The data for this study were collected from both primary and secondary sources. The primary data were collected using a self-administered structured questionnaire from 420 sample households. The semi-structured questionnaire was designed based on the study's objective and a review of related literature on the adoption of ICS technology. After an in-depth literature review and a preliminary qualitative study, the questionnaire was drafted and translated into the local language, Amharic. The questionnaire comprised socio-economic data, household energy use and cooking pattern, kitchen environment and improved stove, and household perception of improved stoves. The questionnaire was pretested with 20 households helped to ensure questionnaire clarity, ordering, the relevance of questions and the time taken for an interview. Hence, appropriate revisions were made to the questionnaire before beginning the actual household surveys. Households were interviewed in their homes by trained data collectors. Before data collection, data collectors and supervisors were trained on data collection tools and how to obtain consent forms from respondents.

The study considered household heads as the primary decision-makers concerning household energy use. The study households were contacted after getting an ethical approval letter from Addis Ababa University. Then, individual informed consent was obtained from potential participants, who were given the right to withdraw or refuse to answer specific

questions at any time. To respect the rights of participants, the researcher examined ethical issues throughout the data collection process. In addition to the household survey, KIIs with nine individuals were conducted to supplement the data. Finally, secondary data were gathered from various published and unpublished sources, including books, journals, and reports, to cross-validate statistical results and support arguments.

4.2.3. Sampling Techniques

A multistage sampling technique was used to select study districts, kebeles, and sample households. First, two districts,[4] namely Adiarkay and Debark, were purposively selected because of the presence of Mirt stove popularization and introduction. Second, based on the information obtained from experts in the selected districts, a list of kebeles[5] and their status concerning Mirt stove use was generated. Accordingly, six kebeles with relatively higher and lower levels of Mirt stove popularization and introductions were selected randomly. Thirdly, lists were collected from each district water and energy office concerning Mirt stove user households. In addition, the list of traditional stove user households was compiled from the district water and energy office and kebele administration. Finally, the number of households included in the survey was determined using the formula suggested by Kothari (2004). Probability proportional to the sample size was used to calculate the number of households sampled from each kebele chosen. Accordingly, data were collected from 420 households using a systematic random sampling technique in each kebele from the sampling frame.

4.2.4. Stove Performance Testing Method

In this study, the kitchen performance test (KPT) was selected over other tests, such as the Water Boiling Test (WBT) and Controlled Cooking Test (CCT), since it more accurately measures the *in-situ* fuel use of the improved stove (Granderson et al., 2009). The Water Boiling Test can control for confounding factors and provides a high degree of replication but does not reflect actual cooking performance. It is most suited to a lab-based screening of stove efficiency (Bailis et al., 2007; Negash et al., 2021). Similarly, the Controlled Cooking Test is less standardized but more realistic than the Water Boiling Test. However, it still does not reflect the actual cooking practice in the field (Negash et al., 2021; Wassie & Adaramola, 2021). The WBT and CCT can be employed as screening procedures to identify inefficient stove designs before disseminating the stove (Chagunda et al., 2017). The relative

[4] District (synonymous with woreda) is the third level of the administrative division of Ethiopia after Zones.
[5] Kebele is the smallest administrative unit in Ethiopia within districts (woreda).

advantages and disadvantages of each test are related to the control of variation (Ochieng et al., 2013).

Although the KPT is difficult to control, leading to data with high variance, it has the advantage of reflecting the actual fuel consumption in the study households as they proceed with baking sessions (Chagunda et al., 2017). The KPT involves the assessment of fuel consumption by households under normal cooking practices (Granderson et al., 2009; Ochieng et al., 2013). The KPT conducted in this study was based on the protocol prepared by Bailis et al. (2007). A cross-sectional approach was used to collect data on fuelwood consumption from two separate groups of households using *Mirt* and traditional three-stone stoves simultaneously. The study was conducted with 15 and 20 purposively selected households of *Mirt* and traditional stove users, respectively. The KPT measures the relative rate of fuelwood consumed by each stove as they are used in the normal household environment (Chagunda et al., 2017). Households that participated in the KPT were not included in the survey. This reduced biases that may have existed if a household had participated in both studies. Willingness to participate in the study was also considered when selecting households. The same type of wood was supplied to each participant's household to minimize variation in influencing factors. The wood was from eucalypts, the preferred fuelwood type at the study site. All the selected participant households were initially instructed to use only weighted wood for baking *injera* over three sessions. This was done through Mirt stoves and a traditional three-stone fire. Besides, the participants were told not to use the fuel given for other tasks.

According to the experimental protocol, the researchers provided three batches of wood to the participant households for three baking sessions. Then, we conducted KPT by measuring the amount of fuelwood consumed in each sample household for three baking sessions. First, three batches of fuelwood were weighed with a pocket balance and recorded. Next, digital wood moisture pins were used to measure the wood’s moisture content. Then, three pieces of wood samples from the stock were randomly selected to determine moisture content using a moisture meter at the top, middle, and bottom parts. The wood remaining from the first baking session was weighted in the second baking session, and the difference was recorded as fuel for the second day. We then measured the moisture content of three randomly selected woody pieces (nearly 10-16% moisture). In session three, the same procedure was repeated. Finally, the mean fuel savings and time spent on baking injera were statistically analysed.

Per capita fuelwood consumption was reported based on standard adult equivalent (SAE) using the guidelines of FAO, 1983): child < 14 years = 0.5, female > 14 years = 0.8, male 15-59 years = 1.0 and male >59 years = 0.8.

The annual fuelwood consumption was extrapolated from the average fuelwood consumption of stoves as outlined by Manaye et al. (2022):

Annual fuelwood consumption $\left(\frac{kg}{year}\right) = \left(\frac{X\ stove}{n}\right)$ * 144 baking session

where: X_{Stove} = average fuelwood consumption per stove (kg) and n = number of days per baking session.

4.2.5. Description of *Mirt* and traditional three-stone fire stove

Mirt, meaning 'best' in Amharic, is a biomass-burning improved stove developed and promoted by the then Ethiopian Rural Energy Development and Promotion Center along with Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) in the first half of the 1990s for baking *injera*[6] (Negash et al., 2021). It is made of mortar – a mixture of scoria (red ash), pumice, or river sand with cement (Fekadu Kedir et al., 2019), with an enclosed chamber for combustion having a small opening for adding biomass fuel and letting in the air (Dresen et al., 2014). *Mirt* stove has six parts joined together (Fig. 13a). Four arcs form the circular combustion chamber, and two U shapes form the circular pot rest (Kedir et al., 2019). *Mirt* stove is circular in shape with an average diameter of 120 cm and height of 75 cm. It has an extra small chamber of 45 cm in width, which is used for resting a pan used for cooking stews (Negash et al., 2021). The traditional three-stone open-fire stove requires three separate stones to support the clay pan (*mitad*) (Tadesse, 2020). The three stones are placed in a triangle to hold the baking pan. The types and sizes of stones used vary depending on the availability of stones (Adem & Ambie, 2017). The three-stone open-fire stove forms a circular structure with an average height of 40 cm (Negash et al., 2021). Since the stones are not fixed, the area can be set relative to the material used for cooking (Fig. 13b).

[6] *Injera* is an Amharic term for Ethiopian thin bread similar to a pancake, usually made from teff.

(a) (b)

Figure 13: (a) Mirt stove and (b) traditional three-stone stove.

4.2.6. Data Analyses

The collected data were edited, coded, and classified before entering into the Statistical Package for Social Scientists (SPSS v.2020) software. The data was then cleaned and checked for errors and inconsistencies before being exported to STATA 14 for analysis. Descriptive analysis: mean, standard deviation, tables, and graphs were employed to describe the variables. Bivariate (χ^2 and t-test) analysis was used to see whether or not *Mirt* improved stove user and non-user households related to demographic and socio-economic variables and institutional factors. A binary logistic regression model was used to identify factors determining the adoption of *Mirt*-improved stoves. The data acquired from KPT was summarized using an Excel spreadsheet developed by Shell Foundation to calculate households' daily fuel consumption and time taken to bake *injera*. In this study, daily refers to the sessional baking day since fuelwood consumption was not measured daily. An Independent sample t-test was used to compare the time taken and fuelwood consumption when households used *Mirt* and traditional stoves.

4.2.7. Model Specification

In this study, adoption refers to households that possess and use functioning *Mirt* stoves, as verified by an enumerator during household surveys. We used adoption of *Mirt* stove as a dependent dichotomous variable since having or not having a *Mirt* stove is a binary decision. To estimate regressions when the dependent variable is dichotomous, taking 0 or 1, there is a need for a probability model that has two features: (1) as X_i increases, $P_i = E\ (Y = 1|\ X)$ increases but never steps outside the 0-1 interval, and (2) the relationship between P_i and X_i

is nonlinear; thus, one can easily use the cumulative distribution function (CDF) (Gujarati, 2004). Both probit and logit regression models satisfy the above two requirements. However, this study used the logit model over the probit model for two practical advantages, as Jose et al. (Jose et al., 2020) specified. The first is its simplicity since the equation of logistic CDF is very simple. The second is its interpretability, i.e., the inverse linearizing transformation for the logit model is directly interpretable as log-odds, while the inverse transformation of probit does not have direct transformation. By considering these advantages, the study used a binary logistic regression model to predict the effects of independent variables on the dependent variable. Thus, a household's *Mirt* stove adoption probability was modelled as a dichotomous variable with values 1 'if a household adopts a *Mirt* stove' and 0 'otherwise'.

Hence, the logistic regression model for estimating the probability of adopting the *Mirt* improved stove (P_i) is specified as follows:

$$\Pr(Y_i = 1) \implies P_i = 1/1 + e^{-zi} = e^{Zi}/1 + e^{Zi}, \text{ where } Z_i = \beta o + \beta_1 X_1 \quad (1)$$

Similarly, the probability of not adopting the *Mirt* stove is specified as follows:

$$\Pr = (Y_i = 0) \implies 1 - P_i = 1/1 + e^{Zi} \quad (2)$$

When dividing equation (1) by (2), it gives the odds ratio:

$$P_i/1 - P_i = e^{Zi} \quad (3)$$

The logit model is a logarithmic transformation of the odds ratio specified as follows:

$$L_i = \ln(P_i/1 - P_i) = z_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \quad (4)$$

where, L_i is the log of odds ratio; P_i- the probability of households' adoption of Mirt stove ranging from 0 and 1; Z_i a function of n-explanatory variables (X_i) β_0 the intercept or a constant term; $\beta_1, \beta_2, \ldots, \beta_k$ –the coefficient (parameter) of independent variables to be estimated; $X_1, X_2, \ldots, X_k$ - independent variables, k- the number of explanatory variables, and ε is the random error. Finally, the model's parameter is estimated using the Maximum Likelihood (ML) method (Gujarati, 2004).

4.2.8. Variables Explaining the Empirical Model

After the analytical procedures are clearly stated, it is necessary to identify the potential explanatory variables that can influence the adoption of *Mirt* stoves. A basic assumption of the adoption of *Mirt* stove technology suggests that factors both internal (e.g., household demographics and socio-economic characteristics) and external (e.g., information campaigns, supply chain development, and support) to households influence decision-making (Jeuland et al., 2015). The nature of these factors is location-specific and varies in different geographical and socio-economic contexts (Muneer & Mohamed, 2003; Jan, 2012; Lewis & Pattanayak, 2012). Thus, based on a review of the literature on the adoption of ICS, previous research findings, and knowledge of experts, the major factors determining the adoption of *Mirt* stoves comprise demographic, social, economic, and institutional factors (Adane et al., 2020; Dresen et al., 2014; Jan et al., 2017; Mehetre et al., 2017; Mengistu et al., 2016; Onyeneke et al., 2017; Wassie & Adaramola, 2021). The variables hypothesized to influence the adoption of *Mirt* stoves, their measurement, and expected signs are presented in Table 18. Since the study used cross-sectional data, there was a need to ensure multicollinearity problems. Hence, the Variance Inflation Factor (VIF) for separate continuous explanatory variables was computed. In addition, the correlation matrix technique was employed to check the degree of association among dummy explanatory variables. The test results show no multicollinearity problem between the variables considered.

Table 18: Definition of explanatory variables supposed to explain household adoption of Mirt stove.

Variables	Type	Definition & Measurement	Expected sign
AGE	Continuous	Age of the household head (years)	+/-
GENDER	Dummy	Sex of the household head: 1: Female & 0: Male	+/-
EDUCATION	Continuous	Years of education of the household head	+
HOUSIZE	Continuous	Number of persons in the household	+/-
OCCUPATION	Dummy	Occupation of the head: 1: farmer & 0: otherwise	
INCOME	Continuous	Annual earnings of household from various sources (salaried, on-farm, non-farm, etc.) (in USD)	+
CREDIT	Dummy	Access to credit service: 1: Yes & 0: otherwise	+
DISTFW	Continuous	Walking distance from home to the fuel source (in mins.)	+
DISTMKT	Continuous	Walking distance to the nearest market to get *Mirt* (mins.)	-
ACCINFON	Dummy	Information about *Mirt* stove: 1: Yes & 0: otherwise	+
HOUSE	Dummy	Type of House: 1: Corrugated & 0: otherwise	+
KITCLOC	Dummy	Kitchen location: 1: separate & 0: Inside living house	+
PERCPRICE	Dummy	Perceived price of *Mirt* stove:1: Expensive & 0: otherwise	-
BENMIRT	Dummy	Fuel saving benefits of *Mirt* stove: 1: Yes & 0: otherwise	+
AVAPROD	Dummy	Availability of *Mirt* stove producer: 1: Yes & 0: otherwise	+
FUELSOURE	Dummy	Household fuel sources: 1: collection & 0: otherwise	-
AWADEFN	Dummy	Awareness about deforestation: 1: Yes & 0: Otherwise	+

4.3. Results and Discussion

4.3.1. Socio-economic Profiles of Households

A total of 420 households were interviewed for the survey, but only 403 were analyzed, resulting in a 96% response rate. The analyses showed that out of the sampled 403 households, about 75% were male-headed, and the remaining 25% were female-headed (Table 19). Among male-headed households, 31% were adopters, while 69% were non-adopters. Of the 102 female-led households, 35% were adopters, and 65% were non-adopters. A comparison of the user and non-user households regarding their age reveals that the users were older than the non-user households. The mean age of all sample households was 46.7, and the mean age of adopter households was 49.7, which was slightly above the mean age of all sampled households. However, the mean age of non-adopter households (45.6) was less than that of adopter households. The result also showed that Mirt stove

adopters spent an average of 7.1 years in school, while the non-adopters spent an average of 4.4 years. Additionally, the average family size of the adopter households was about 6.4 persons, while that of the non-adopters was 5.5 years (Table 19).

Table 19: Association between discrete variables and adoption of Mirt stove.

Discrete variables	All (n=403)	Adopter (n=135)	Non-adopter (n=268)	χ^2
GENDER	Female	36 (35%)	64 (65%)	4.11**
	Male	75 (31%)	226 (69%)	
OCCUPATION	Salaried employed	61 (46%)	71 (54%)	34.28***
	Farming	50 (18%)	221 (82%)	
HOUSE	Corrugated iron roof	109 (36%)	190 (64%)	46.10***
	Thatched roof	2 (2%)	102 (98%)	
KITCLOC	Separate	100 (40%)	151 (60%)	50.43***
	Inside living house	11 (7%)	141 (93%)	
CREDIT	Yes	63 (43%)	82 (57%)	28.71***
	No	48 (19%)	210 (81%)	
ACCINFON	Yes	105 (35%)	191 (65%)	35.12***
	No	6 (6%)	101 (94%)	
AVAPROD	Yes	43 (29%)	103 (71%)	0.42
	No	68 (24%)	189 (75%)	
PERCPRICE	Expensive	63 (23%)	211 (77%)	8.88**
	Cheap	48 (37%)	81 (63%)	
FUELSOU	Collection	74 (23%)	247 (77%)	15.94***
	Buying	37 (45%)	45 (55%)	
BENMIRT	Yes	108 (32%)	231 (68%)	19.91***
	No	3 (5%)	61 (95%)	
AWADEFN	Yes	70 (29%)	175 (71%)	0.33
	No	41 (26%)	117 (74%)	

*, **, and *** significant at 10%, 5% and 1%, respectively

The adoption of Mirt stoves was also influenced by household income. The results showed adopter households had an average annual income of 21,122 ETB (554.4 USD), relatively higher than the average annual income of non-adopter (16,982 ETB or 445.7 USD). Similarly, the results showed that 77% of the non-adopter households perceived that Mirt stoves were expensive; hence, they could not afford them, but 63% of the respondents thought the price was cheap. On the contrary, regarding adopter households, 37% perceived the price was cheap, and 23% stated the price was expensive (Table 20). Besides, 43% and

40% of the adopter households had access to credit services and a separate kitchen, respectively, which was significantly lower than the non-adopters ($p < 0.05$).

Overall, *Mirt* stove adopter and non-adopter households had statistically significant mean differences in age, education, household size, and annual income (Table 20). Similarly, the Pearson chi-square independence test revealed that there was a statistically significant association between Mirt stove adoption and sex, occupation, types of houses, availability of separate kitchens, credit, access to information, perceptions of the stove price, kitchen, fuel sources, and knowledge of the health benefits (Table 19).

Table 20: Association between continuous variables and adoption of Mirt stove.

Continuous variables	Mean(±SD) of all households	Mean (±SD) of the adopter households	Mean (±SD) of non-adopter households	t-value
AGE	46.7 (±11.8)	49.7 (±10.4)	45.6 (±12.2)	-3.100**
EDUCATION	4.6 (±3.4)	7.1(±2.9)	4.4(±3.3)	-7.504***
HOUSIZE	5.7 (±1.7)	6.4 (±1.5)	5.5 (±1.8)	-4.969***
INCOME	18,122 (±9,965)	21,122 (±10,754)	16,982 (±9,419.9)	-3.787**
DISTMKT	168 (±88.9)	47 (±15.6)	176 (±89.8)	2.990**
DISTFW	147.8 (±83.5)	155.9 (±88.2)	144.6 (±79.6)	-1.206

Source: Field Survey (2021). *, **, and *** significant at 10%, 5% and 1%, respectively.

4.3.2. Estimating Fuelwood Consumption Using KPT

The number of people fed has a relationship to the amount of *injera* baked and the fuel needed to prepare *injera*. As the number of people increases, so does the consumption of injera and fuelwood. It was, thus, important to know the number of people eating during the KPT. The KPT results revealed that except for males over 59 years, the t-test analysis showed no significant difference ($p > 0.05$) in the number of individuals participating during mealtime in all age categories between *Mirt* and traditional three-stone stoves (Table 21). Besides, the KPT analysis showed that household size (measured in SAE) ranged from 2.8 to 6.8 persons for three-stone stove users and 4.1 to 7.3 persons for *Mirt* stove users. The overall average household size was 5.7 (±SD = 0.9) for three-stone stove users, while it was 5.4 (±SD = 1.0) for *Mirt* stove users; however, it was not significant ($p > 0.05$).

Table 21: Average fuelwood use, time-saving and adult equivalent of *Mirt* and 3-stone stoves.

Variables	Open-fire stove Mean (±SD)	Mirt-improved stove Mean (±SD)
Average fuelwood use/injera baking session (in kg)	13.24 (±0.82) ***	7.85 (±0.3) ***
Average time-saving/injera baking session (in minutes)	82.7 (±2.2) ***	59.2 (±2.5) ***
Number of adult equivalents	5.7 (±0.9)	5.4 (±1.0)
List of gender and age		
Children: 0-14	1.3 (±0.4)	1.5 (±0.5)
Females: >14	1.6 (±0.6)	1.7 (±0.5)
Males: 15-59	2.3 (±0.9)	2.1 (±0.8)
Males:>59	0.5 (±0.5) ***	0.1 (±0.3) ***
Average fuelwood consumption/injera baking session/SAE	2.4 (±0.4) ***	1.5 (±0.3) ***

Field Survey (2021): *, **, and *** significant at 10%, 5% and 1%, respectively.

The KPT analysis also showed that the amount of fuelwood consumed per SAE using a three-stone stove is significantly higher than that of *Mirt* stove users (t-test: 7.54; df:33; $p < 0.01$) (Table 21), suggesting that the *Mirt* stove saves about 5.4 kg of fuelwood/*injera* baking session (Fig. 4). As a result, each household consumes nearly 1,907 kg of fuelwood per year using a three-sone stove, whereas it was about 1,130 kg of fuelwood annually when a *Mirt* stove used. This translates to a 40.7% (777 kg) reduction in fuelwood consumption when the *Mirt* stove is compared with the three-stone stove. Besides, the remaining thermal energy of the *Mirt* stove after the *injera* preparation is often used to prepare various foods for breakfast. The fuel-saving performance of the *Mirt* stove over the traditional three-stone stove was in agreement with the findings of Dresen et al. (2014) and Negash et al. (2021), who found that the *Mirt* injera baking stove saved 40% and 45% of fuel when compared to a three-stone open fire stove. However, the findings of this study were higher than those of Gizachew & Tolera (2018) in the Bale Eco-Region and Manaye et al. (2022) in the Tigray region, who reported the use of the *Mirt* stove had reduced fuel consumption by 29% and 35% compared to the traditional stove, respectively.

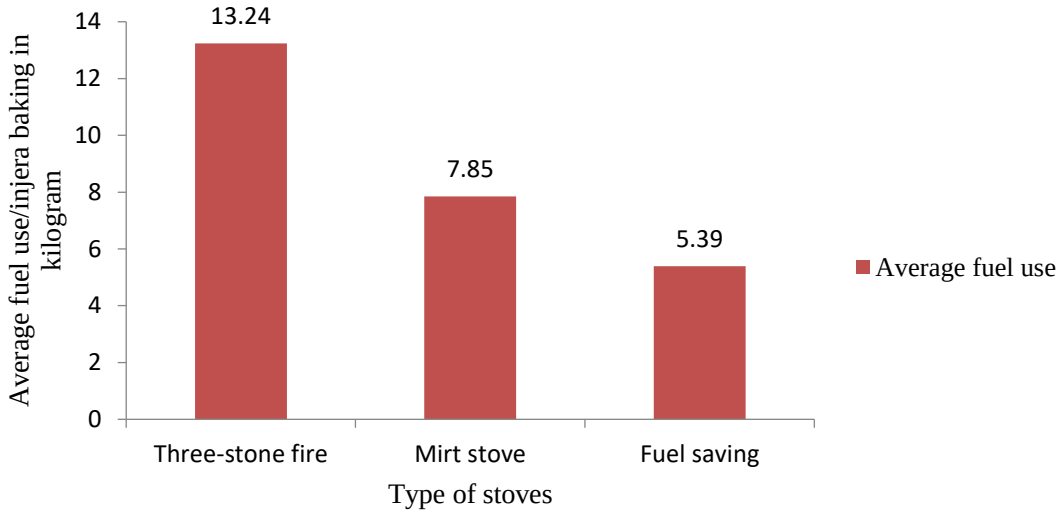

Figure 14: Performance of Mirt compared with three-stone stove in fuel saving. Source: Field survey (2021).

Similarly, the average time spent[7] per *injera* baking session was estimated. The analysis revealed variations in *injera* baking duration, which was longer when a three-stone stove was employed (Table 21). The KPT results showed that the average time to bake *injera* with a three-stone stove was 82.7 minutes (±SD = 2.2) per *injera* baking session, while a *Mirt* stove took around 59.2 minutes (±SD = 2.5) per injera baking session (Table 20). According to the KPT results, the duration of baking *injera* with three-stone stoves is significantly higher than that of *Mirt* stoves (t-test = 29.5; df = 33; $p < 0.01$). The results also revealed that using the *Mirt* stove resulted in a time saving of 23.5 minutes (~28.4%) compared with the three-stone stove (Fig. 15). Our results are consistent with the findings of Gebreegziabher et al. (2018), Wassie & Adaramola (2021) and Manaye et al. (2022), who documented that using improved *Mirt* stoves can save baking time.

[7] Total cooking time is the time in minutes between t_i when the baking injera begins and t_f when the baking injera is completed. It is calculated using: Δt (minute) = t_f - t_i.

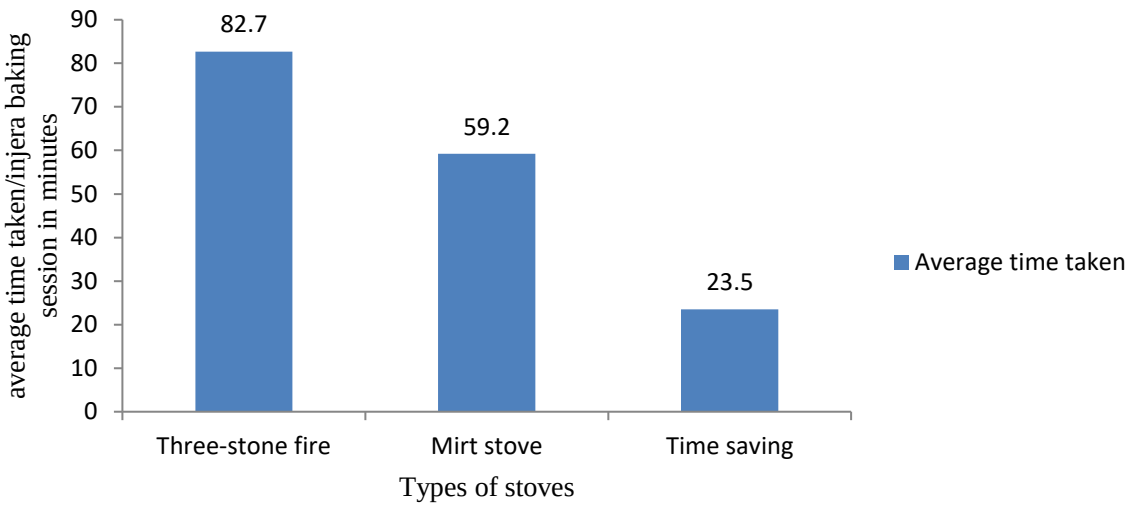

Figure 15: Performance of Mirt compared to three-stone stove in saving time.

Source: Field survey (2021).

4.3.3. Adoption status of improved *Mirt* stoves

The descriptive statistics of the dependent variable (Mirt stove adoption) indicated that only 27% of the sample households in the study area used Mirt improved cookstove. The majority (73%) of the sample households used traditional three-stone stoves as their primary domestic use (Fig. 14). This suggests that efforts of the Government and other stakeholders to promote and disseminate fuel-efficient technologies are still very low. However, a closer examination of the adoption patterns across districts revealed variations in the adoption of improved *Mirt* stoves. In the Debark *District*, for instance, the adoption of *Mirt* stoves as primary stoves had increased (92% or 102 adopter households). This is possibly attributable to the availability of *Mirt* stove producers, the proximity to the stove market, and the high fuel price, leading to the local population adopting *Mirt*-improved stoves. In contrast, the adoption of improved stoves is low (i.e., 8% or nine adopter households) in the Adi-Arkay *District*, owing to the availability of forest resources, lack of availability of stove producers, and the distance from the market, as confirmed by key informants during the interview.

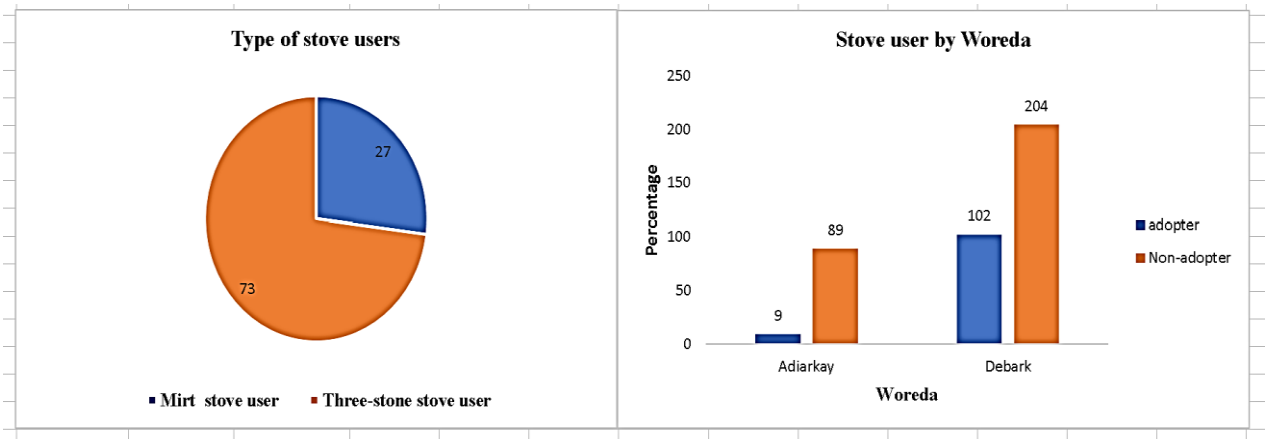

Figure 16: Types of stoves used for baking injera in the study districts.
Source: Field Survey (2021)

4.3.4. Determinants of *Mirt*-Improved Stove Adoption

The estimated results of the binary logistic regression model indicated that the model reasonably fit the observed data. The log-likelihood of the fitted model was -134.09, implying that the model converged and the predictors used in the regression significantly differed from zero. In addition, the estimated LR χ^2 (17) test was 206.21, indicating that all the parameters were jointly significant at 1%. Therefore, the model had a good fit. A non-significant value ($p > 0.05$) of the Hosmer-Lemeshow test (Chi2 = 8.09, df = 10 and p-value = 0.425) is one rule of thumb in validating the 'goodness of fit' of the logistic model (Roger Tarling, 2009). Moreover, McFadden's Pseudo R-squared (Pseudo R^2) is 0.44, showing that the model's explanatory power was relatively good as it was above the statistical threshold value of 20%, as suggested by Kabir et al. (2013). Measures of goodness of fit of the model results revealed that the independent variables were simultaneously related to the log odds of *Mirt* stove adoption. The results further demonstrated that the model correctly predicted 82.4% of the overall household sample. The analysis suggests that eleven variables were significant in determining households' adoption of *Mirt* stoves among the seventeen hypothesized explanatory variables included in the model. The results of the binary logistic regression model are presented in Table 22.

Age of a household head had a positive and significant ($p < 0.01$) effect on *Mirt* stove adoption. This means the probability of older household heads adopting *Mirt* stove is higher than their younger counterparts. As the age of the household head increases by one year, the odds ratio of *Mirt* stove adoption increases by 1.05. The probable reason might be explained by the fact that households with older heads accumulate wealth over time, enabling them to

adopt *Mirt* stoves and change their cooking behaviour (Muneer & Mohamed, 2003; Onyeneke et al., 2017; Mamuye et al., 2018). In addition, older people need more convenient energy technology because they are not as strong as younger to travel a long distance to collect biomass fuels (Rahut, Mottaleb, et al., 2017). Our result is consistent with the findings of Gebreegziabher et al. (2018) in Ethiopia and Brooks et al. (2016) in India, who reported that older household heads were more willing to adopt ICSs than younger household heads. In contrast, our findings differ from those of Lewis & Pattanayak (2012), who documented that younger household heads make adoption decisions superior to older household heads since they are more open to new technologies.

Sex of household head is one of the predictor variables with significant ($p < 0.01$) and positive effects on *Mirt* stove adoption. The positive relationship indicates that female-headed households increased the likelihood of *Mirt* stove adoption by a factor of 2.89 compared with their male-headed counterparts. The reason might be that women are the victims of the adverse effects of traditional stoves and energy deficiency since they spend most of their time in cooking and collecting fuel. The finding is comparable with the findings of other authors (Woubishet, 2009; Gebreegziabher et al., 2012; Beyene & Koch, 2013; Gizachew & Tolera, 2018; Adane et al., 2020), who documented that female-headed households are more likely to adopt improved stoves compared with their male counterparts. However, empirical studies revealed that women often lack sufficient authority and economic power within the household to impose the decision to adopt (van der Kroon et al., 2014; Vigolo et al., 2018; Karanja & Gasparatos, 2019; Kisiangani et al., 2022;) and are, thus, less likely to adopt ICS.

The education level of the household head had a statistically significant ($p < 0.01$) positive effect on adopting a *Mirt* stove, implying that the odds of adopting a *Mirt* stove increased by 1.21 times as the educational level of the household head increased by one schooling year. The probable reason might be that better education enhances understanding of unclean fuels' harmful health effects and makes households conscious of the environmental effects of increased traditional stoves (Daniel, 2020). Besides, education shapes one's thoughts and perceptions, making them rational and capable of analyzing the benefits of ICS technologies and adoption (Walekhwa et al., 2009; Shallo et al., 2020). A review of different studies has shown that education level significantly determines ICS adoption (Lewis & Pattanayak, 2012; Rehfuess et al., 2014; Brooks et al., 2016; Puzzolo et al., 2016; Jan et al., 2017). The

finding is also similar to the work of previous studies (Woubishet, 2009; Beyene & Koch, 2013; Alamir, 2014; Gebreegziabher et al., 2018; Gizachew & Tolera, 2018; Kassa et al., 2020), which reported that educational level was associated with improved stove adoption.

Household size is also an essential factor determining the adoption of ICS. The results show household size was found to have a significant ($p < 0.1$) and positive influence on the adoption of *Mirt* improved stove. More specifically, as family size increases by one person, the odds ratio of adopting a *Mirt* stove increases by a factor of 1.24. The possible explanation might be that larger household sizes need more demand for *injera*, which, in turn, requires more fuel, and to reduce expense, they tend to adopt improved stoves. However, various views arose among scholars regarding the effect of family size on ICS adoption. For instance, van der Kroon et al. (2014) suggested that a large family size means abundant labour for fuel collection necessary for traditional stove users, thus, reducing the intention to adopt ICS. Similarly, Brooks et al. (2016) explained that ICS is perceived as too small for large families. Conversely, other studies reported that larger families are more likely to adopt ICS. Onyeneke et al. (2017), for instance, suggested that cooking for large family sizes requires more time and fuel. Hence, large families tend to adopt more fuel-saving technologies than small families. The finding is consistent with studies conducted in Ethiopia and elsewhere in developing countries (Pine et al., 2011; Gizachew & Tolera, 2018; Marie et al., 2021; Yayeh et al., 2021) in which household size was reported to have a significant positive association with *Mirt* stove adoption. However, it contradicts the findings of other authors (Alamir, 2014; Rehfuess et al., 2014; van der Kroon et al., 2014), who reported that large family size implies additional labour for fuel collection and negatively influences the adoption of improved stoves.

The results further show a significant ($p < 0.01$) and positive association between living in a modern house and adopting a *Mirt*-improved stove. This implies that those living in a modern corrugated iron house were about twenty-three times more likely to adopt a *Mirt*-improved stove than households with a traditional house. The probable reason might be that having a house constructed with a corrugated roof is considered a sign of economic status and modernization, implying that possessing it is associated with higher socio-economic status. As household socio-economic status improves, houses will likely be renovated and equipped with modern and improved stoves. This result is similar to the finding of previous

authors (Michael, 2015; Shen et al., 2015), who reported that the type of house in which the households reside is associated with improved stove adoption.

Table 22: Binary logistic regression model results on factors affecting *Mirt* stove adoption.

Adoption of *Mirt* (Y_i)	Coef.	Std. Err.	z value	P value	Odds Ratio
AGE	0.049	0.017	2.90	0.010***	1.05
GENDER (1 = Female)	1.062	0.385	2.76	0.010***	2.89
EDUCATION	0.187	0.056	3.32	0.010***	1.216
HOUSIZE	0.211	0.112	1.88	0.060*	1.235
OCCUPATION (1 = farming)	-0.441	0.352	-1.25	0.210	0.644
LogINCOME	-0.589	0.815	-0.72	0.706	0.555
LogDISTMKT	-1.024	0.571	-1.79	0.05**	0.784
LogDISTFW	-0.743	0.702	-1.06	0.290	0.476
HOUSE (1 = corrugated roof)	3.129	0.799	3.92	0.010***	22.85
KITCLOC (1 = separate)	1.147	0.356	3.22	0.010***	3.121
CREDIT (Yes = 1)	1.102	0.324	3.41	0.001***	3.010
ACCINFON (Yes = 1)	0.918	0.518	1.77	0.077*	2.504
AVAPROD (1 = Yes)	0.122	0.353	0.35	0.730	1.130
PERCPRICE (1 = Expensive)	-0.575	0.448	-1.28	0.11	0.563
FUELSOU (1 = collected)	-0.719	0.382	-1.88	0.06**	0.487
BENMIRT (1 = Yes)	1.768	0.672	2.63	0.01***	5.859
AWADEFN (1 = Yes)	0.278	0.336	0.83	0.408	1.321
cons	-8.223	4.469	-1.84	0.066	

*, **, and *** significant at 10%, 5%, and 1%, respectively

Consistent with our expectations, access to credit had significantly ($p < 0.01$) and positively affected *Mirt* improved stove adoption. This implies that households with access to credit facilities increased the probability of *Mirt* stove adoption by a factor of 3.01 compared with households without access to credit. A possible explanation might be that access to credit enables the poor to finance the upfront costs of stove adoption. The result is consistent with the findings of earlier authors (Lewis & Pattanayak, 2012; Berhe et al., 2017; Karanja & Gasparatos, 2019), who reported a positive association between access to credit and improved stove adoption.

Exposure of households to information significantly ($p < 0.05$) and positively influenced improved stove adoption. *Ceteris paribus*, having access to information by households increased the odds of adopting *Mirt* stove by a factor of 2.5 compared with their counterparts. The possible explanation is that access to ICS information from various communication channels (e.g., TV, radio, posters, mobile message) at the grass-root level strengthened the

awareness and knowledge of the communities about new technologies. The result is supported by previous studies (Legesse et al., 2015; Onyeneke et al., 2017; Yayeh et al., 2021), which found that ICS technology adoption is higher among households with information and awareness through various communication means than their counterparts.

A household's source of fuel also influences the adoption of *Mirt* stoves significantly ($p < 0.1$) and negatively. The study found that households who collected fuelwood are less likely to adopt *Mirt* stoves compared to those who get fuel through purchasing. The odds ratio of *Mirt* stove adoption of households who collected fuelwood was lower by a factor of 0.487 compared to those who get fuelwood through purchasing. The probable reason for the present finding might be the availability of accessible forest sources in the study site. Thus, it can be inferred that the cost spent for fuelwood triggers households to look for alternative technology and, hence, adopt fuel-efficient stoves. The findings of this study are in agreement with relevant literature in Ethiopia (Mengistu et al., 2016; Mamuye et al., 2018; Adane et al., 2020; Yayeh et al., 2021) and elsewhere in developing countries (Pine et al., 2011; Jan, 2012), which reported that households who collected fuelwood were less likely to adopt improved stoves.

The availability of a separate kitchen room positively and significantly ($p < 0.01$) influenced improved stove adoption. This means households with a separate kitchen increase the odds of adopting *Mirt* improved stove by a factor of 3.12 compared with their counterparts. A possible explanation could be that *Mirt* stoves require additional space because they are fixed in nature and larger in size than other improved biomass stoves. Hence, a separate kitchen is necessary to place *Mirt* improved stove with a chimney. The result is consistent with the finding of other authors (Alamir, 2014; Puzzolo et al., 2016; Gizachew & Tolera, 2018), which reported that having a separate kitchen increases the probability of adopting a *Mirt* stove. However, the result is inconsistent with the finding of Woubishet (2009), which found that the effect of separate kitchens was insignificant in determining improved stove adoption.

As hypothesized, distance to the stove market negatively and significantly ($p < 0.1$) affects the likelihood of adoption. This indicates that with a unit increase in the distance to the stove market, the odds of adopting a *Mirt* stove decrease by a factor of 0.784, holding other variables constant. The probable reason is that distance could affect the accessibility of new technologies and information, resulting in a negative relationship. The result is consistent

with other studies in Ethiopia (Legesse et al., 2015; Marie et al., 2021; Yayeh et al., 2021), which reported a negative association between improved stoves and distance to the market.

Knowledge of the fuel-saving benefits positively and significantly ($p < 0.01$) explained the likelihood of adopting the *Mirt* stove. As households' perception of fuel-saving benefits increased, the odds of adopting a *Mirt* stove increased by a factor of 5.859 compared with their counterparts. The possible explanation for this finding could be the greater value given to the fuel-saving benefits of the *Mirt* stove by the study communities due to saving the amount of fuel required, fuel gathering time, and cooking time. The finding is consistent with similar studies in Ethiopia and elsewhere in developing countries (Gebreegziabher et al., 2012; Lewis & Pattanayak, 2012; Adane et al., 2020; Wassie & Adaramola, 2021), which documented a positive association between knowledge of fuel-saving benefits and improved stove adoption. However, contrary to our finding, a study by Nepal et al. (2011) reported a negative relationship between fuel-saving benefits and improved stove adoption. The probable reason might be the rebound effect. When the improved stoves reduce fuelwood demand in the first place, it would lower the shadow price of fuelwood. A lower shadow price could, in turn, prompt households to consume more fuelwood.

4.4. Conclusions and Policy Implications

Access to clean, modern, reliable, and sustainable energy sources remains limited for many individuals in developing countries such as Ethiopia. By using improved cooking stoves such as *Mirt*, it is possible to tackle the recurring challenges of energy poverty, environmental crises, health problems, and agricultural productivity. This study aimed to examine the effectiveness of *Mirt* stoves in terms of saving fuel and time and identify the factors that determine the adoption of *Mirt* stoves in the Semien Mountains and adjacent districts in Northwest Ethiopia. The KPT analysis also showed that the amount of fuelwood consumed per SAE using a three-stone stove is significantly higher than that of *Mirt* stove users, suggesting that the *Mirt* stove saves about 5.4 kg of fuelwood/*injera* baking session. This reduced the burden on the forests, women and children during fuelwood collection, school participation and other associated opportunity costs. Similarly, the average time spent per *injera* baking session was estimated. The analysis revealed variations in *injera* baking duration, which was longer when a three-stone stove was employed. The results further showed that using the *Mirt* stove resulted in a time saving of 23.5 minutes (~28.4%) compared with the three-stone stove.

However, three stone stoves are still the preferred cooking technology over the *Mirt* stove in the study area. The survey results show that several socio-economic, environmental and institutional factors contributed to the low adoption rates of *Mirt* stoves. A deeper understanding of the interaction between factors of *Mirt* stove adoption and stove efficiency can provide a solid evidence base for developing policies and practical solutions to achieve clean cooking in the study area and elsewhere in Ethiopia. After a thorough analyses, we identified barriers, such as market, credit, infrastructure and awareness, and socio-economic barriers to adopting *Mirt* improved stoves. In addition, the study found a lack of demand, whereas distribution, promotion and marketing were also significant factors in determining successful stove adoption. Overall, *Mirt* stoves can substantially reduce deforestation, fuelwood collection time and baking time if used sustainably and effectively. Moreover, if improved stoves are used regularly, they can increase the school attendance of children and participation of women in income-generating activities because women and children are usually in charge of household cooking and fuel collection.

Based on the findings, the study suggests: (i) there is a need to increase awareness of the potential benefits of using *Mirt*-improved stoves to improve livelihoods and reduce deforestation and indoor air pollution; (ii) when creating and implementing better stove technology for clean cooking, it's important for planners and policymakers to consider key factors such as revitalizing the supply chain through market development to encourage the adoption of improved stoves; (c) Finally, it is of utmost importance that the government takes immediate action to promote improved stove technologies like *Mirt*. Using these technologies not only conserve energy but also contribute to reducing deforestation, emissions and health problems caused by elevated concentration of pollutants in the kitchen when using inefficient three-stone stoves.

However, this study was limited to only *Mirt* stove, examining the effectiveness of *Mirt*-improved stove in fuel and time-saving and identifying factors that influence its adoption. There are some important issues that require further investigation in the future. These include examining the effect of *Mirt* stoves on indoor air quality, finding ways to enhance the local supply chains for stoves produced in the study area, and exploring the possibility of increasing local production of stoves verified to save fuel and improve air quality and health.

CHAPTER FIVE: FUELWOOD COLLECTION AND CHILDREN'S SCHOOL ATTENDANCE: EVIDENCE FROM NORTHWEST ETHIOPIA

ABSTRACT

Fuelwood collection is part of the daily routine of many households in Sub-Saharan Africa. Most of the collection burden usually falls on children and women, diverting their time from education and income-generating activities. This study examines the link between fuelwood collection work and children's school attendance in the Semien Mountains and adjacent districts in Northwestern Ethiopia. The study employed cross-sectional data using 679 children aged 7 to 17 collected from 403 households. Descriptive and econometric models were used to analyze the data. The results revealed that children spend about 7 hours per week on fuelwood collection. On the other hand, the results showed that around 77% of children of school age were delayed when they entered grade one. The regression results indicate that household characteristics, such as female headship, age and education level, have a positive and significant effect on children's fuelwood collection work. The intensity of fuelwood collection and children's school attendance were also influenced by child characteristics: age, sex, and birth order. Besides, the results revealed that with a 5% increase in fuelwood collection intensity, the probability of children's school attendance reduces by about 25%. This means that collecting fuelwood for an extra hour per week leads to a decrease of over 2% in the likelihood of children's school attendance. The results suggest that children's school attendance is affected by fuelwood collection work. Based on the findings, the study recommends policy interventions for influencing school attendance and natural resource recovery.

Keywords: Child; Collection; Endogeneity; Fuelwood; Intensity; Participation; Schooling

5.1. Introduction

Human capital development is crucial for poverty reduction (Assaad et al., 2010) and for laying the foundation for a better and prosperous nation (Psacharopoulos & Yang, 1991). This requires substantial investment on child education by parents (Cuesta, 2018), as it allows for self-advancement and improvement in the future (Eigbiremolen, 2017). Investment in education, particularly child education, contributes to a more enlightened and productive society while breaking the intergenerational cycle of poverty and deprivation (Ravallion & Wodon, 2000; Krueger & Maleckova, 2002; Dimoso, 2012). In addition, investing in education can help to increase economic growth, productivity and national development (Burkea and Beegle, 2004; Ndiritu & Nyangena, 2011; Gebremedhin & Mohanty, 2016). Thus, education benefits not only the individual but the entire society through various spillover effects (Assaad et al., 2010). Recognizing the importance of human capital development in economic growth has prompted many developing-country governments to invest in education (Ndiritu and Nyangena, 2011).

Despite considerable efforts to increase investment in education, millions of school-age children in Sub-Saharan African (SSA) countries are not in school, and many others leave school at a young age and often learn little while in school (Abafita & Kim, 2015). Instead, many children are involved in hidden forms of child labour, like work in the household, on the family farm, or in the family business (Webbink et al., 2012). Domestic chores, such as fuelwood and water collection, are often not included in employment statistics, resulting in limited knowledge about the children who perform these tasks (Webbink et al., 2012; Levison et al., 2018). As a result, excluding the dimension of domestic child labour grossly underestimates the welfare effects of work on school-aged children (Assaad et al., 2010).

Studies indicate that child labour is a major impediment to the development of SSA (Beyene et al., 2014). According to the UNICEF (2021) report, nearly 86.6 million (23.9%) children in SSA are child labourers. Out of these, about 72% of children aged 5 to 17 are engaged in child labour within their family unit. Besides, in SSA, about 32 million children between 6-11 years old are out of school due to domestic work at home (UNISCO-UIS, 2019). Spending considerable time doing domestic chores unrelated to schooling might affect children's school attendance (Rossi, 2001; Ndiritu and Nyangena, 2011; Cuesta, 2018). Given the scale of this problem, it is essential to gain insight into its determinants so that policies aimed at reducing it can be developed.

Households in many SSA countries face a challenge in accessing energy sources readily (Aggarwal et al., 2001). As a result, they heavily rely on collecting environmental products like fuelwood to meet their daily fuel needs (Cooke, 1998; Agesa & Agesa, 2019). A disproportionate share of the collection burden falls on women and children, particularly school-aged children (Cooke, 2000; Aggarwal et al., 2001), spending many hours each week collecting fuelwood for cooking (Nankhuni & Findeis, 2004). When deforestation makes fuelwood scarce, women and children are forced to travel long distances and invest significant time and labour (Budds et al., 2001; Dimoso, 2009; Rogers, 2014). As reported by Cundale et al. (2017) and Beyene et al. (2014), in SSA, the time spent collecting fuelwood ranges from 4 to 15 hours per week, depending on the level of deforestation. As a result, children at prime school attendance age routinely collect fuelwood for at least as many hours as adults (Ndiritu and Nyangena, 2011). Accordingly, children are more valuable than adults in fuelwood collection activities, which may increase their value (Aggarwal et al., 2001; Winkler-Dworak, 2004). This situation, however, reduces children's school attendance, study time, and, ultimately, their ability to learn and progress through school (Levison et al., 2018), which has detrimental effects on future human capital development (Koissy-Kpein, 2012).

Several studies have been conducted in developing countries to examine the link between child labour and various indicators of educational outcomes. Most of the analyses have focused on the effects of formal child labour on education, but there is no consensus. On the one hand, some studies have found that child labour is detrimental to children's education (Psacharopoulos, 1997; Heady, 2003; Ray & Lancaster, 2005; Arends-Kuenning et al., 2009). In contrast, other studies have shown that child labour has no detrimental impact on education (Patrinos & Psacharopoulos, 1997; Ravallion & Wodon, 2000).

However, little attention has been given to what happens to children's school attendance following the decline in the availability of environmental products due to deforestation. Very few studies have quantified the effect of environmental degradation on children's schooling in SSA. For example, Nankhuni & Findeis (2004) documented that Malawian children are significantly involved in resource collection work, and their likelihood of attending school decreases with increased hours allocated to this work. Similarly, Ndiritu and Nyangena (2011) found that children in Kenya who spent more than two hours collecting water or fuelwood were 21% less likely to attend school. In Ghana, Porter et al. (2012) also reported children's lateness to school owing to water fetching, adversely affecting school attendance and performance.

The situation is similar in Ethiopia, where about 71% of children aged 5 to 17 years were engaged in some work supporting their households' livelihoods (ILO, 2018). Even preschool children, who are usually too young to work, participate in domestic and farm work activities (Admassie, 2003). In addition, at the national level, Ethiopia has struggled to improve primary education. For instance, the government subsidizes the direct cost of primary school to alleviate the financial burden placed on low-income households in sending their children to school (Woldehanna & Araya, 2016). However, Ethiopia remains far from achieving its goal of universal primary education and has one of the world's lowest school enrolment rates (Haile & Haile, 2012). An additional and worrying challenge is that even where educational resources are made available, some communities do not fully value children's education. This manifests in low primary-school completion rates, gender disparities in enrolment and grade attainment (Admassie, 2003; Cuesta, 2018; Chanie, 2018) and children's delayed school attendance (Woldehanna, 2011). Besides, although the official age for primary school enrolment is seven years, the average starting age is over seven years (FDRE-MoE, 2021).

A large share of the Ethiopian population heavily depends on the natural environment for their livelihoods (Baye, 2017). At the same time, the environment that supports people's livelihoods and well-being is being degraded (Nyssen et al., 2004). The problem is severe in the Northwest highlands (Belayneh et al., 2018). Evidence shows that natural forests are deforested owing to a long history of settlement, rapid population growth, agricultural land expansion, the escalating demand for fuelwood, and urbanization (Amsalu et al., 2007; Wondie et al., 2011; Worku et al., 2016; Agidew & Singh, 2017; Miheretu & Yimer, 2017; Belay & Mengistu, 2019). In addition, deteriorating forest resources would affect children's school attendance since they collect and transport fuelwood, which costs more time and labour (Gebru & Bezu, 2013). Thus, the value of children for fuelwood collection increases (Beyene et al., 2014).

Moreover, whether a child should attend school or work at home is primarily a parental decision. Hence, parental attitudes towards educational investment are important to school attendance (Admassie, 2003). However, although schooling increases future earnings, poor parents do not send their children to school due to a lack of financial resources to cover the direct costs of sending children to school and the opportunity cost of the children's time (Glewwe, 2002). Various authors have reported that different factors contribute to the low likelihood of children's school attendance, of which domestic child labour is the most prominent (Admassie, 2002; Admassie & Bedi, 2003; Haile & Haile, 2012; Mussa et al.,

2017). However, most previous studies on child labour and education were general and did not demonstrate the negative impact of natural resource scarcity on children's education.

Several studies have examined the extent of environmental degradation in Ethiopia (Belay Tegene, 2002; Bewket, 2002; Nyssen et al., 2004). However, empirical studies on how hours of work spent by children in fuelwood collection activities affect their likelihood of attending school have yet to be conducted in the study area. Only two studies in Ethiopia have quantified the link between natural resource scarcity and children's schooling. The first study was conducted by Gebru & Bezu (2013), who used cross-sectional data on children aged 7 to 18 to investigate the effects of natural resource scarcity on children's education in Tigray. They found that a 50% increase in resource collection intensity reduces the likelihood of a child attending school by approximately 11%. The second study was carried out by Beyene et al. (2014), who explored the effect of resource collection on child education using panel data collected in four rounds from the Amhara region. They concluded that natural resource scarcity negatively contributes to child education by increasing the work burden on children.

Many children in the study area spend substantial time collecting environmental products, including fuelwood, water and other household chores. While increasing attention is being paid to the fuelwood scarcity problem and deforestation, the interaction between natural resource scarcity and children's primary education has largely been overlooked. Numerous factors contribute to these concerns about impediments to children's educational attainment, many of which have been studied. However, attention has yet to be given to children as fuelwood collectors in Northwest Ethiopia, where resources are thinly spread. The present study empirically tests the hypothesis that deteriorating environmental products negatively affect children's schooling. Therefore, this study aimed to examine the effects of fuelwood collection on children's school attendance in northwest Ethiopia, specifically whether relying on fuelwood for household energy causes children to miss school.

5.2. Materials and Methods

5.2.1. Description of the Study Area

The study was conducted in the Semien Mountains and adjacent districts of North Gondar Zone, Amhara National Regional State, Northwest Ethiopia. The Semien Mountains are located at latitude 13°29'21" to 13°29'40" N and longitude 37°51'36" to 38°34'33" E. It lies within five *woredas* (*districts*), including Adiarkay, Debark, Janamora, Beyeda, and Telemet,

covering an area of 241,093 hectares (Debebe et al., 2023). The total population was estimated to be 378,929 (CSA, 2020), with an average household size of 6.01 (AWF, 2019). Demographic trends since the 1950s have revealed a doubling of the population every 25 years, resulting in deforestation, farmland scarcity and shortening fallow periods on shifting cultivation land (Hurni & Ludi, 2000). In addition, most of the population (>80%) use fuelwood as their main energy source for cooking, contributing to deforestation and forest degradation (ANRS, 2007). The altitude of the study area ranges from 1,276 to 4,540 m (Debebe et al., 2023). Altitudinal variations in the Semien Mountains have given rise to a number of rare and endemic animal and plant species (Debonnet, 2006). The study area is located in one of the wettest and coldest regions of the country, with a mean annual rainfall of between 1,350 and 1,550 mm falling in a single rainy season, whereby the highest amount of precipitation is between June and September (Hurni & Ludi, 2000). Mean daily temperatures range from a minimum of -2.5°C to 4°C to a maximum of 11°C to 18°C (Asrat et al., 2012). The area is drained and divided into different landscape features by tributaries of the Tekeze River, such as the Ansiya, Jinbar, Belegez, and Mesheha (Yohannes et al., 2020). The dominant vegetation type in the study area comprises the Afro-montane Erica forest (*Erica arborea*), hypericum woodland, ericaceous heath-land and the Afro-montane grassland (Wondie et al., 2011; Asrat et al., 2012). Approximately 84% of the population is rural, living primarily on subsistence agriculture (AWF, 2019).

5.2.2. Research Design, Data Sources and Methods of Data Collection

This study accessed data from both primary and secondary sources using a cross-sectional research design. First, primary data were gathered from parents (household heads) regarding school-age children using a semi-structured questionnaire. Semi-structured interview questionnaires were chosen because they could include quantitative and qualitative questions. Then, after an in-depth literature review and a preliminary qualitative study, a survey questionnaire was drafted and translated into the local language, Amharic. Finally, the questionnaire was pretested with 20 households to ensure questionnaire clarity, ordering, relevance, and interview time. The survey data collected provide evidence on children's involvement in education and fuelwood collection, hours spent by children on fuelwood collection, collection intensity, school attendance, grade-for-age, household demographic and socioeconomic characteristics and sources of fuelwood collection, and time spent on other domestic chores. Besides, various location indicators, including distance from the main

road, distance to the nearest market, distance to the nearest forest, and distance to the nearest primary school, were collected.

Before data collection, six enumerators were recruited and trained on the issues behind the selection of school-age children and data-gathering techniques. In addition, parents or household heads were interviewed on behalf of school-age children. Because this study aims to understand the effect of children's participation in fuelwood collection on their education, the study focused on children aged 7-18 (inclusive). Therefore, we chose seven years as the lower limit since most children begin elementary school when they are seven or older (FDRE-MoE, 2021). Similarly, the maximum age limit was chosen following the 1999 International Labour Organization's (ILO) convention, which defines all persons under the age of 18 as children (ILO, 1999). In addition, four key informant interviews were administered with zonal, district and kebele level education experts and school teachers to get insight into children's school attendance and attainment.

Throughout this study, the authors adhered to ethical standards and principles. First, the study participants were contacted after getting an institutional approval letter from Addis Ababa University. Then, individual informed consent was obtained from potential participants, who were given the right to withdraw or refuse to answer specific questions at any time. To respect the rights of participants, the researcher attempted to examine ethical issues throughout data collection. Furthermore, secondary data were collected from different published and unpublished sources, including books, journal articles, office reports and records, magazines, and internet sources, to cross-validate the results and support the arguments.

5.2.3. Sampling Techniques

We employed a multistage sampling technique to select the study site, *districts*, *kebeles* and sample households. First, the Semien Mountains were chosen as a study site on purpose. This is because it is one of the most environmentally degraded areas of the Amhara region, suggesting that a slight change in forest resources can have far-reaching consequences for the livelihoods of local communities and associated forest products. In the second stage, two *districts* surrounding the Semien Mountains, *Adiarkay* and *Debark*, were deliberately chosen to ensure variation in the characteristics of the *districts*, including agroecology and forest cover. In the third stage, six *kebeles* from the selected *districts* were randomly selected. Finally, a simple random sampling technique was used to determine sample households. The

kebele administration of each *kebele* provided household lists. As a result, 420 households were chosen randomly from the sampling frame in each *kebele* using a systematic random sampling technique based on a formula proposed by Kothari (2004). Then, probability proportional to size was employed to calculate the number of households sampled from each kebele chosen.

5.2.4. Data Analyses

The collected data were edited, coded, and classified before entering into the Statistical Package for Social Scientists (SPSS v.2020) software. The data was then cleaned and checked for errors and inconsistencies before being exported to STATA 14 for analysis. Finally, in line with the study's objective, we use descriptive statistics such as mean, standard deviation, tables and figures to describe the effect of children's participation in fuelwood collection on educational attainment. A bivariate probit model was also used to examine the effect of fuelwood collection work on children's school attendance.

5.2.5. Theoretical framework

Theoretically, this study is based on Becker's (1965) seminal paper on time allocation and its extensions to household behaviour to study schooling and fuelwood collection work. A family's decision regarding child schooling, resource collection, and other activities can be analyzed with the household production model developed by Becker (1965). The model assumes that parents' utility maximization is constrained by market-purchased goods and time endowment. This model necessitates joint decisions on the number of children a family should have, as well as the pattern of time allocation among household members for schooling, market work, and household production (Gebru & Bezu, 2013). In the model's original specification, home-produced goods (e.g., collected fuelwood in this study) and market goods (e.g., electricity) are perfect substitutes for each other. Gronau (1977) further developed the model by arguing that a household's home goods production is characterized by diminishing marginal productivity due to tiredness and limited access to local forest resources. This is also validated by Rosenzweig and Evenson's (1977) conclusion that a family's decision on children's time allocation to school and work are jointly determined. The preference of the household for schooling (S), leisure (L), home-produced goods (Z), and a composite consumption commodity (C) is specified as follows:

$$U = U (S, Z, L, C, E)$$

where U = the utility function of the family, and E = the household environment. The utility function is assumed to be concave and twice and continuously differentiable. Z refers to goods produced at home, using market-purchased goods and children's housework time, such as collecting fuelwood, taking care of younger siblings, tending animals etc. In this model, parents maximize a utility function, subject to time and budget constraints.

5.2.6. Econometric Model Specification

Parents are responsible for allocating their children's time between various activities (Woldehanna et al., 2017). For instance, households are likely to decide between child labour, schooling, and fuelwood collection and call for modelling simultaneous equations (O'Brien et al., 2019). In this study, school attendance is potentially endogenous, which may lead to a biased and inconsistent result. One possible channel of endogeneity is that school attendance and fuelwood collection can be jointly determined through labour supply decisions (Ndiritu and Nyangena, 2011). The decision to send children to school may be jointly determined with a decision to send children to collect fuelwood. This problem is addressed by estimating a simultaneous equation model for binary variables. Following Nankhuni & Findeis (2004), Ndiritu and Nyangena (2011) and Gebru & Bezu (2013), this study adopted a bivariate probit model[8] to examine the interactions between fuelwood collection and schooling. The generic form of the bivariate probit model is

$$\mathrm{Y}_{\mathrm{i1}}^{*} = \beta_1 \mathrm{X}_{i1} + \varepsilon_{\mathrm{i1}} \quad (1)$$

$$\mathrm{Y}_{\mathrm{i2}}^{*} = \beta_1 \mathrm{X}_{i2} + \varepsilon_{\mathrm{i2}} \quad (2)$$

Then, the bivariate probit model specifies the observed outcomes to be, as outlined by Greene (2005), which can be written as:

$$Y_{i1} = \begin{cases} 1 \; if \; Y_{i1}^{*} > 0 \\ 0, otherwise \end{cases} \quad (3)$$

$$Y_{i2} = \begin{cases} 1 \; if \; Y_{i2}^{*} > 0 \\ 0, otherwise \end{cases} \quad (4)$$

The bivariate probit model can be written as

$$P(y_1 = \mathrm{i}, = \mathrm{y}_2 = j) = \Phi_2 \, (\mathrm{X}_1 \beta_1, \, \mathrm{X}_2 \, \beta_2, \, \rho) \quad (5)$$

[8] A bivariate probit model is a joint model for two binary dependent variables whose error terms are assumed to be correlated.

where individual observations of y_1 and y_2 are available for all *i*; Y_{i1} and Y_{i2} are the choices of school attendance and participation in fuelwood collection work observed in the data; Y_{i1}^* and Y_{i2}^* are the latent variables[9] from which the decision to participate in these two choices is defined; $X_{i1}$and X_{i2} are the set of explanatory variables determining fuelwood collection work and school attendance; $\beta_1$and β_2 are vectors of coefficients to be estimated; ε_{i1} and ε_{i2} are the error terms in the school attendance and participation in fuelwood collection, respectively. They are assumed to be independently and identically distributed as bivariate probit normal [$\varepsilon_{i1,}$ $\varepsilon_{i2,}$ ρ] ~ bivariate normal (BVN). ρ stands for the correlation coefficient between the error of schooling and fuelwood participation equations.

School attendance and fuelwood collection work are likely to be jointly decided, and error terms are correlated. A test of the jointness of the two decisions is, therefore, a test of the significance of ρ. If the ρ coefficient is statistically significant, the two choices are determined jointly, and the bivariate probit model is estimated first. In contrast, if the ρ coefficient is not statistically significant, the univariate probit model provides consistent estimates (Greene, 1998).

Given the link between school attendance and fuelwood collection work, there are reasons to suspect the recursive Bivariate Probit Regression. Bivariate Probit Regression is a method with two probit equations whose error terms are correlated. One of the binary dependent variables becomes an endogenous regressor variable for the other dependent variable (Greene, 2003). Since children's time spent collecting fuelwood increases as forest resources decline, their likelihood of attending school may be negatively affected. Hence, school attendance may be influenced by the amount of time a child spends on fuelwood collection work (collection intensity). Fuelwood collection intensity is thus an endogenous explanatory variable in the schooling equation.

$$Y_{i1} = \beta_{i1} X_{i1} + \omega Y_{i3} + \varepsilon_{i1} \quad (6)$$

$$Y_{i2} = \beta_{i2} X_{i2} + \varepsilon_{i2} \quad (7)$$

where schooling (Y_{i1}) is a binary variable indicating school attendance of individual *i*, fuelwood (Y_{i2}) is a measure of fuelwood collection work, Y_{i3} stands for the collection intensity for the child *i* introduced as a continuous variable in the school attendance model and ω its coefficient.

[9] A latent variable is a variable that is incompletely observed (Seyoum, 2018)

The methods for estimating coefficients in equations 6 and 7 depend on which fuelwood measure we use. We use a binary variable to measure *schooling*, indicating whether child *i* is currently enrolled when collecting fuelwood. The average time spent collecting fuelwood is measured as a continuous variable. Therefore, equation 6 can be considered a probit model with a continuous endogenous regressor. In equation 6, interdependence arises between Y_{i1}(school attendance) and Y_{i3} (fuelwood collection intensity) since Y_{i3} appears on the right-hand side of equation (6). To address the endogeneity problem, the two-stage conditional maximum likelihood (2SCML) models are used, as outlined by Rivers & Vuong (1988). The technique works well if at least one endogenous and continuous explanatory variable exists in the probit model (Greene, 1998). The process of 2SCML computation involves two steps. First, a reduced form Ordinary Least Squares (OLS) regression is estimated on fuelwood collection intensity (equation 7) as a function of all exogenous explanatory variables and the instrumental variable (IV), and then residuals are saved. Following that, both the saved residuals and the endogenous collection intensity variables are included in the schooling probit equation. If the simple t-statistic for the estimated coefficient of the residual is statistically significant, it suggests that collection intensity is endogenous in the school attendance probit (Wooldridge, 2002).

To estimate the structural form equation for the school attendance model (equation 6) and the reduced form equation for the fuelwood collection intensity model (equation 7), the following process is used:

$$Y_{i3} = \theta' X_{i3} + \delta Z + \epsilon_{i3} \qquad (8)$$

where X_i refers to the common exogenous covariates in both equations; Z is an instrumental variable (IV) that affects fuelwood collection intensity in equation 7 without directly entering the schooling probit in equation 6.

To accurately identify the coefficients, it's necessary to have valid instruments, Z_i, that is independent of the error terms. These instruments should only affect the decision to collect fuelwood and not directly impact the decision to pursue education. Previous studies have attempted to find valid instruments for measuring collection intensity. For instance, Nankhuni & Findeis (2004) used wood and water scarcity variables and access to own-piped water as instruments to measure collection intensity. Similarly, Ndiritu & Nyangena (2011) utilized household fuel expenditure and the proportion of children collecting fuelwood in a household relative to its size as valid instruments. In addition, Gebru & Bezu (2013) also

utilized the number of donkeys possessed by a household. In this study, we used the children-to-family size ratio proposed by Ndiritu & Nyangena (2011) as a valid instrument of fuelwood collection intensity to estimate the effect of fuelwood collection activities on children's school attendance. This is because compared with a single child, the higher the ratio of children to the family size, the lesser the burden to collect fuelwood, which can directly affect the intensity of fuelwood collection. Consequently, this may also indirectly affect their school attendance.

5.2.7. Description of Variables and Hypothesis

In this study, the dependent variables are schooling, fuelwood collection, and the average time spent collecting fuelwood. Schooling is a binary variable indicating whether the child is enrolled in school. Fuelwood collection participation is also a binary variable that indicates whether the child participated in fuelwood collection in the last week before the survey. Finally, the intensity of fuelwood collection is measured as a continuous variable, which is determined by the number of hours spent collecting fuelwood per week. As previously stated, children participate in different activities, such as farm work, resource collection, schooling, etc. Because the objective of this study is to examine the effect of children's participation in fuelwood collection on their school attendance, the following discussion is limited to child fuelwood collection work. Moreover, several explanatory variables are hypothesized to influence children's school attendance and fuelwood collection. These could include household characteristics such as the age, sex, size, income, and education level of the household head, as well as individual child characteristics: age, sex, birth order, current school attendance, age at first class, grade-for-age and time spent in fuelwood collection (Table 23).

Table 23: Definition of explanatory variables supposed to explain the dependent variables.

Variables	Type	Definition and measurement	Expected sign
Dependent variables			
FW_COLL	Dummy	Child participated in fuelwood collection work: 1: Yes; 0: Otherwise	
Log (COLL_INT)	Continuous	Weekly time spent collecting fuelwood by a child (in minutes)	
SCHOOL	Dummy	Child currently attends school: 1: Yes; 0: Otherwise	
Independent variables			
Child characteristics			
AGE_CHILD	Continuous	Child age (in years)	+
SEX_CHILD	Dummy	Sex of child: 1: Male; 0: otherwise	-
BIRTH_ORD	Dummy	Child Birth order (in order)	-
Household characteristics			
SEX_HEAD	Dummy	Sex of the head: 1: Male; 0: otherwise	+/-
AGE_HEAD	Continuous	Age of the head (in years)	-
YEAR_EDU	Continuous	Years of education (years)	-
HOUSE_SIZE	Continuous	Number of individuals in the family	+
OCCUP_HEAD	Dummy	Occupation of the head: 1: Farming; 0: Otherwise	-
INCOME	Continuous	Income of the head (Birr)	+
DIST_FOR	Continuous	Distance to the forest (in minutes)	-
DIST_SCH	Continuous	Walking distance to school (in minutes)	+
WOREDA	Dummy	A child lives in Debark 1; 0 Otherwise	-

5.3. Results and Discussion

5.3.1. Socio-economic Characteristics of Households

Table 24 shows the basic summary statistics of the variables for the sample households involved in the study. We sampled and interviewed a total of 420 households and achieved a response rate of 96%. The survey data revealed that about 75% of the households are headed by males, while 25% are female-headed. The mean age of the household head is 45.2 years, with 5.2 average years of schooling. The average household size is 5.52 persons. This is higher than the regional average of 4.3 in Amhara (CSA, 2008). On average, there were approximately 2.5 children per household. Households have an average annual income of about 18,123 ETB (about US$ 470.36[10]) from various sources. When it comes to occupation, nearly two-thirds of the sample households are engaged in farming, and over a third are self-

[10] During data analysis, the official exchange rate was US$1=38.53 ETB

employed. In addition, roughly 64% of households lack access to electricity, while the remaining 36% have access. On average, households spend around 69 minutes travelling to access nearby forest resources. Many households rely heavily on biomass fuel, specifically fuelwood, as their primary source of energy for household purposes.

Table 24: Summary statistics of households' demographic and socioeconomic characteristics.

Variables	Mean	SD
Gender (Male =1; Female= 0)	0.747	0.435
Age of the household head (years)	45.21	11.418
Schooling of the head (years)	5.17	3.381
Household Size (number of persons)	5.19	1.827
Annual income of the household (Birr)	18,123	9,966
Occupation of the household head (Farming=1; Others=0)	0.67	0.469
Children in the household (numbers)	2.51	1.284
Fuelwood as a primary source of energy (Yes=1; No=0)	87.5	0.33
Electricity connection (Yes=1; No=0)	0.365	0.482
Distance to the nearest forest (minutes)	69.12	37.69
Distance to primary school (minutes)	37.83	24.13

Source: Field Survey (2021)

5.3.2. Children's Schooling and Fuelwood Collection Work

The statistical summary in Table 25 displays the participation of school-aged children in fuelwood collection and their school attendance. The sample encompasses 679 children aged 7 to 17 who live with their biological parents, which is the primary focus of this study. All the children came from households that participated in the survey. Children usually begin their primary education at the age of seven and are expected to finish it by the time they turn 15 (Woldehanna & Araya, 2016). Of the 679 school-aged children, 55% (374) are males, while 45% (305) are females. The average age of children is around 12.6 years.

Table 25: Summary statistics of school-age children in the households.

Variable	Mean	SD
School attendance (Yes=1; No=0)	0.79	0.406
Fuelwood collection participation (Yes=1; No=0)	0.81	0.394
Fuelwood collection intensity per week (minutes)	406.7	172.4
Sex of the child (Male=1; Female=0)	0.55	0.498
Age of the child (years)	12.55	2.998
Birth order of the child (numbers)	3.31	1.68
Ratio of children who collect fuelwood to family size	0.372	0.128
Grade of the child (years)	5.272	2.164
Grade-for-Age (GAGE) (enrolled at age 7=1; enrolled over age 7=0)	0.236	0.425
Absent from class (Yes=1; No=0)	0.77	0.422
Age at first class/grade (numbers)	8.60	1.196
Fuelwood collection trip (days)	2.34	0.458

Source: Field Survey (2021)

The proportion of children in the sample who had been enrolled in school was 79% at the time of the survey, consistent with the net enrolment rate of the Amhara Region (78.5%) but lower than the national average (86.4%) (FDRE-MoE, 2021). Average years of schooling were 5.3 years, suggesting many children do not finish primary education. The results also indicated that 21% of children are out of school (Table 24). The 21% who did not attend school had dropped out permanently or temporarily. If they were to attend school the next academic year, they would need to repeat their current grade level. There are multiple reasons why students may not be able to attend classes during the academic year. It is evident that 32% of school-aged children are unable to attend school due to the need to collect fuelwood. Additionally, 28% and 22% of children cannot attend school because of farm work and lack of parental interest in education, respectively (Fig. 17). According to key informant participants, it has been identified that one of the reasons for children not being able to attend school is due to the financial constraints faced by households in affording the cost of education.

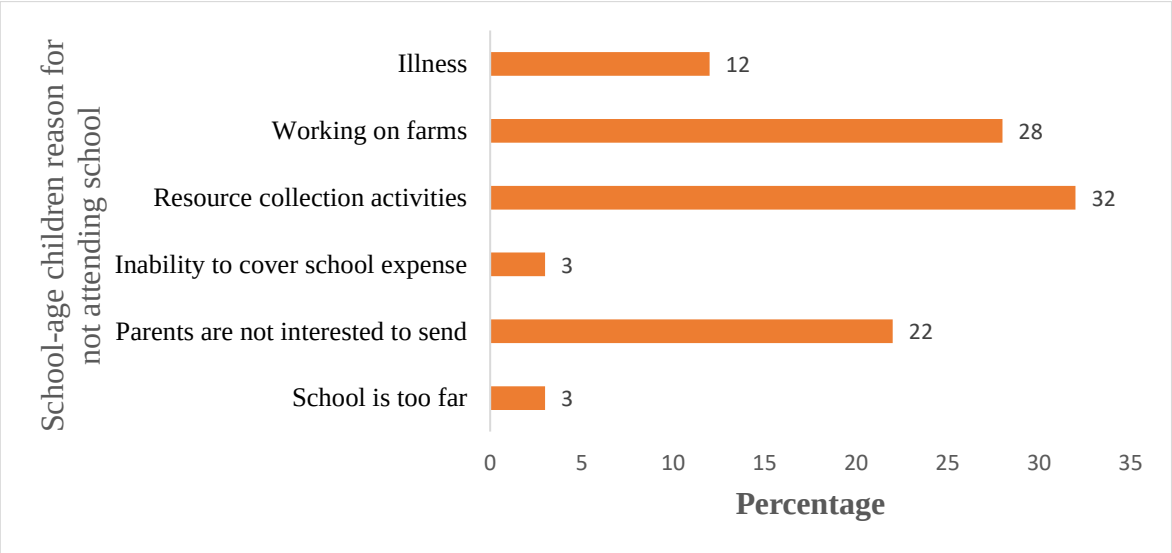

Figure 17: Reasons for school-age children not attending school.

Apart from permitted holidays and school breaks, those students who attended school during the semester were occasionally absent from class. The results found that 77% of students were absent from school, while 23% never missed class (Table 25). The respondents also reported that a considerable number of students missed class, with 46% absent for about ten days, 41% absent for 11 to 20 days, and 13% absent for over 20 days per semester (Fig. 18).

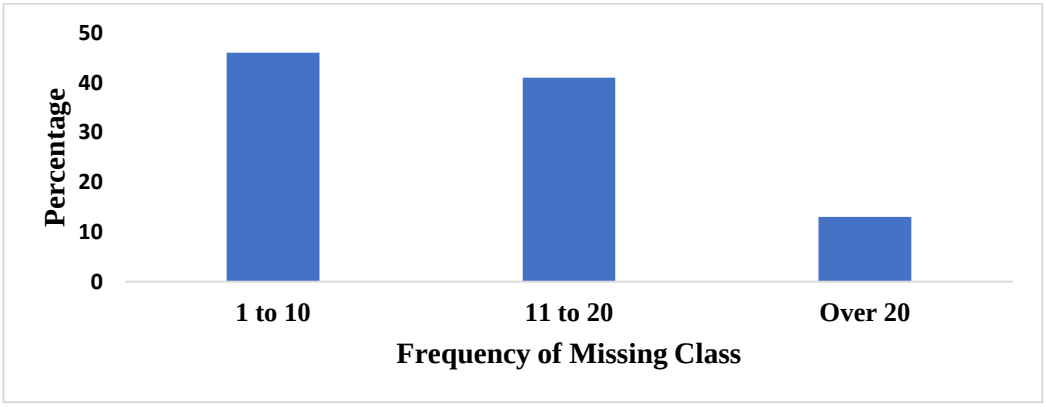

Figure 18: Frequency of missing class during the academic year.

As the kebele education expert indicated, each kebele in the research area had at least one primary school. These schools are public, and children rarely attended primary schools outside their kebele. According to Kebele education expert, on average, children spend around 30 hours per week on their schooling, which includes time spent travelling to and from school, attending class time, and completing homework. Figure 19 depicts the percentage distribution of school-aged children across different classes. It can be seen that most school-aged children in the survey households are in grade 8 (21%), followed by grade 7 (15%), grade 6 (14%), and grade 5. These are relatively physically fit pupils, and their

labour is crucial in helping their parents with domestic work farm activities, collecting fuelwood, and fetching water. However, grade 8 students, though mature, might not be largely available for domestic chores since they are preparing themselves for the general grade 8 regional examination. Their daily school schedules might also be very tight. While the lower enrolment rates in grade one suggest that some children may start school late due to household chores (Fig. 19).

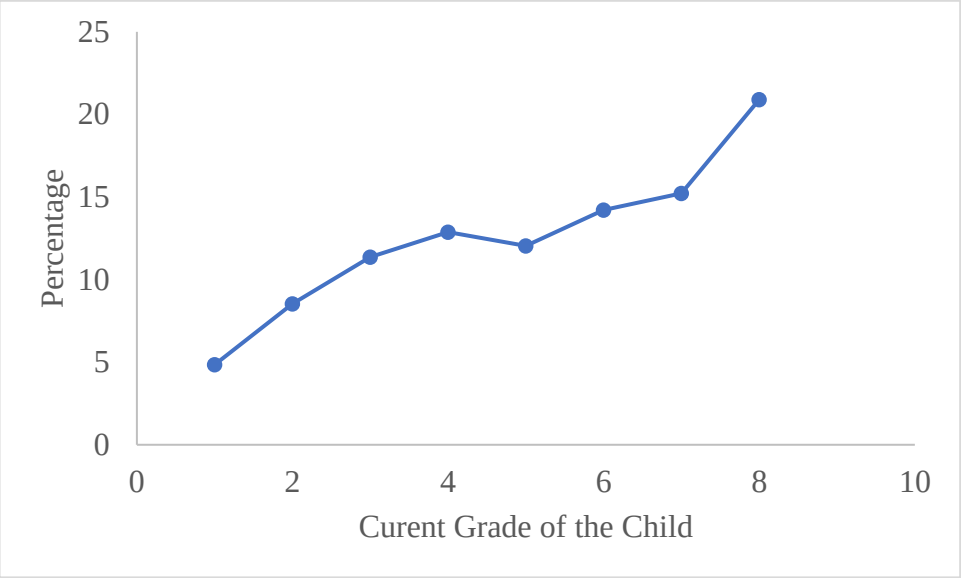

Figure 19: Percent distribution of school-age children across classes.

On the other hand, school-going children might be engaged in collecting resources. The results indicate that a sizeable percentage of school-age children (64%) are involved in both tasks, while 20% and 13% were engaged in fuelwood collection and schooling only, respectively (Fig. 20). This may be the manifestation of natural resource scarcity, which may induce children to gather resources for domestic use and even for market purposes. Compared to their sub-sample, about 17.7% of the male children participated only in schooling, while 22% solely engaged in fuelwood collection tasks. In comparison, about 70% of male children combined both fuelwood collection work and schooling. In contrast, 16% of female children were involved in schooling only, while 19% participated in resource collection work.

Moreover, children make an average of 2.34 trips per week to gather fuelwood. On average, children spend nearly 407.7 minutes (6.8 hours) per week collecting fuelwood, which includes travel and collection time. This task is particularly time-consuming for them (*see* Table 25). Spending hours collecting fuelwood can have a negative impact on children's

school attendance. Consistent school attendance is crucial to achieving good grades and progressing at the right age for class. The results show a notable association between children's school attendance and participation in fuelwood collection activities (*see* Table 3). In addition, male children are more likely to participate in fuelwood collection tasks and attend school than female children.

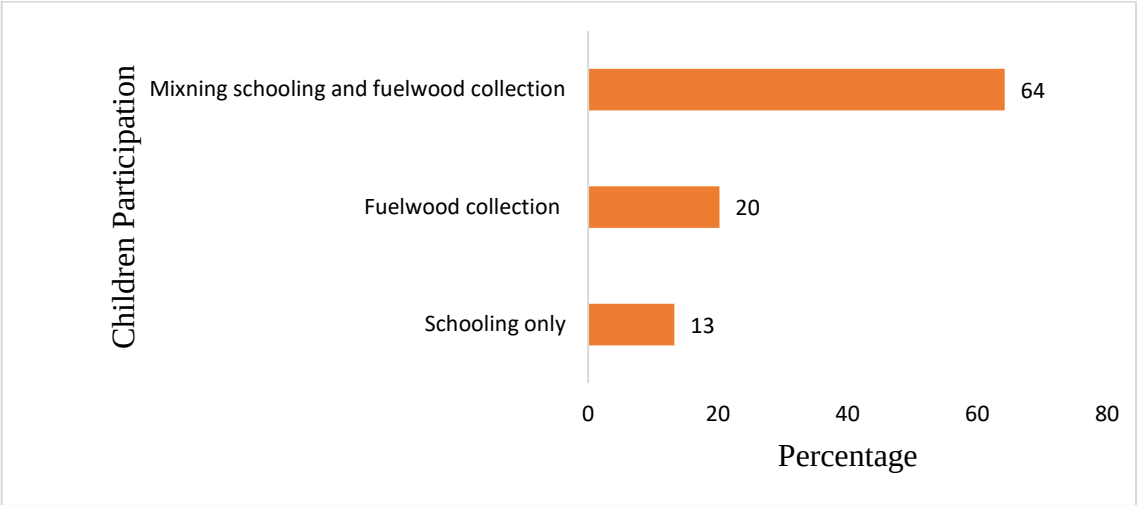

Figure 20: School-age children's participation in fuelwood collection and schooling

Even though the expected age for children to start school is 7, we still have students older than seven years in our dataset because some children start grade 1 later than seven years. Our results show that only 23.3% of school-aged children started grade 1 at age seven, as required by the education system in Ethiopia. On the other hand, the result shows that approximately 77% of children of school age were delayed when they entered grade 1 (Table 25). The implication of delaying starting school reduces efficiency and negatively affects children's motivation for schooling (Abafita & Kim, 2015). Interestingly, the results reveal that about 23% of students started grade 1 at age 8, 30% at 9, 17% at 10, and 6% at 11 (Fig. 21a). There are several reasons why some children start grade 1 late, such as fuelwood collection (44%), Farm work (26%), domestic work burden (22%), and parents' lack of interest in education (9%) (see Fig. 21b).

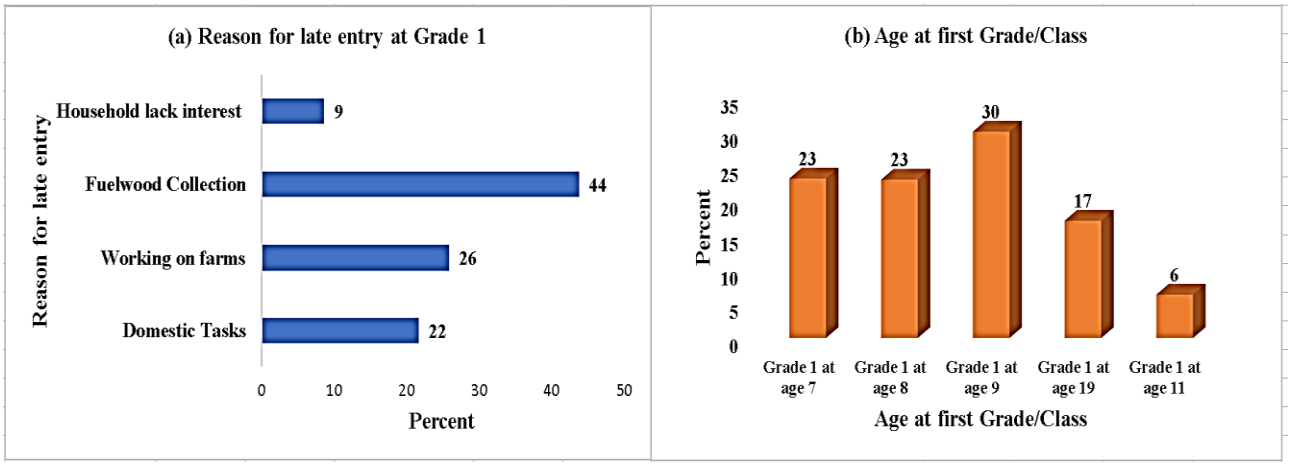

Figure 21: (a) Reason for late entry at grade 1 (b) School-aged children age at first class.

The survey results display that about 16% (108) of children were found to have dropped out. This might be attributed to domestic work (40.6%), followed by farm work (40.2%) and resource collection work (17.4%) (Fig. 22).

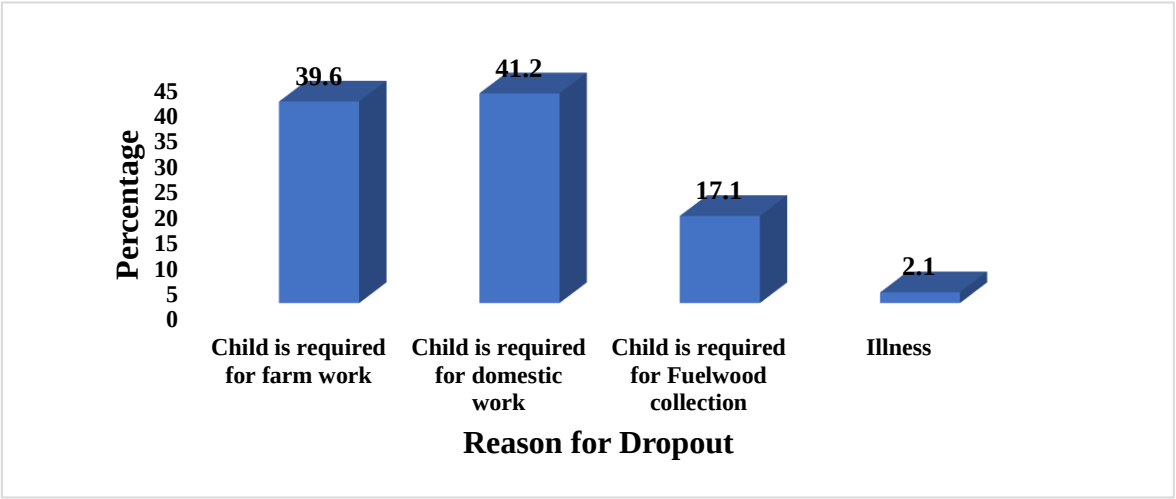

Figure 22: School-aged children's reason for dropout.

Table 25 also presents the effects of resource collection on children's school attainment. Of the children involved in resource collection work, 84% reported that resource collection affected their school attainment, as reflected by class absence (39%), followed by the low performance (29%), lack of time to complete assignments (13.4%) and drop out (7.4%) (*see* Fig. 23). Key informant teachers and experts also confirmed that fuelwood collection and other household chores affected students' school attendance.

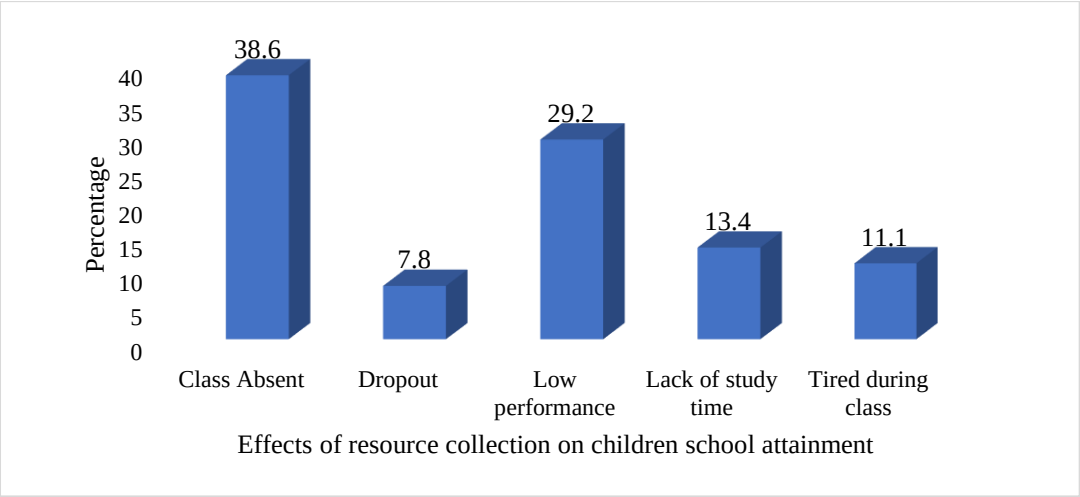

Figure 23: Effects of fuelwood collection on children's school attendance.

Moreover, during the survey, households were asked about their fuelwood sources. About 87% of the households have identified forests as an essential source of fuelwood. The results (Fig. 24) further show that about 54% of the household obtained fuelwood from state and community forests, followed by on-farm trees (33.3%) and purchasing from the market (12.7%). In the same vein, households were asked if fuelwood supply was a problem in the study area. This was usually indicated by travel time and distance to the fuelwood source. Time per trip can be used to measure resource scarcity, as Filmer & Pritchett (1996) suggested. Consequently, fuelwood sources determine the average travel time as well as the collection time needed to gather fuelwood.

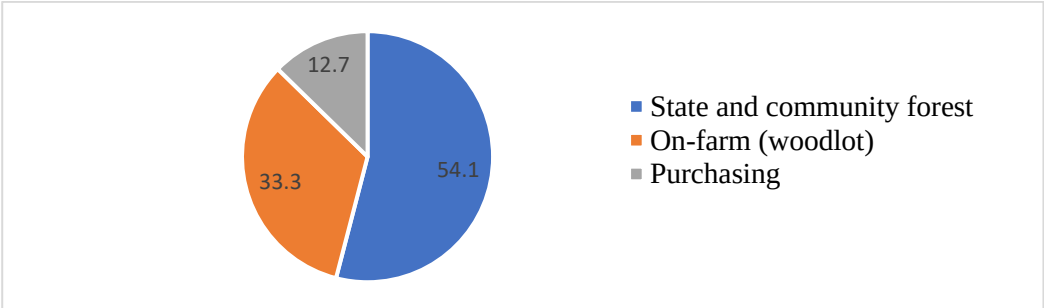

Figure 24: Sources of fuelwood for households.

5.3.3. Determinants of Children's Fuelwood Collection Intensity

The bivariate probit model for school attendance and fuelwood collection participation work produced a Wald test of rho = 0 (chi2 (1) = 17.22; Prob > 0.000), indicating that there is a correlation between the disturbance terms of the equations. Thus, unexplained factors that affect children's participation in fuelwood collection and schooling decisions are positively correlated. Thus, fuelwood collection participation and school attendance appear to be competing activities. The finding of this study supports the joint estimation of the

participation in fuelwood collection and schooling equation and aligns with other studies of a similar kind (Nankhuni & Findeis, 2004; Ndiritu and Nyangena, 2011; Gebru & Bezu, 2013).

The estimated univariate probit of fuelwood collection work participation, fuelwood collection intensity (first stage regression), and the school attendance instrumental variable probit are shown in Table 26. The second column in Table 26 shows results from estimating the reduced form of the fuelwood collection intensity equation. On the other hand, the first and third column displays results from the probit model for the school attendance and fuelwood collection participation equations. Residuals from the fuelwood collection intensity equation are added as an additional regressor to the schooling model to control and test for the endogeneity of fuelwood collection intensity.

The Ordinary Least Square regression of the fuelwood collection intensity model provides an R^2 of 0.383. This indicates that 38% of the variability in fuelwood collection intensity can be explained by the explanatory variables included in the model, suggesting the model fits the data reasonably well. Furthermore, an F-test of the hypothesis that the ratio of the child-to-family size has no effect on the other variables gives a test statistic of 10.2, suggesting a strong instrument.

The first stage estimation (the fuelwood collection intensity) in the 2SCML technique displays the ratio of the child-to-family size used as an instrument for the endogenous log (fuelwood collection work hours) variable (Table 26). The instrument used in the fuelwood collection model is significant and hence relevant. We found a negative relationship between the ratio of children (who collect fuelwood) to family size and fuelwood collection work intensity (-0.787), suggesting that the number of children and fuelwood collection intensity is negatively correlated. This indicates that households with an extra child will likely reduce the average hour spent gathering fuelwood per week by 79%, assuming all other things remain constant. Nevertheless, the negative relationship between the child-to-family size ratio and time spent collecting fuelwood is consistent with our expectations based on past empirical studies and theoretical models of household allocation (Ndiritu and Nyangena, 2011; Gebru & Bezu, 2013).

Household characteristics variables affect the likelihood of participating in fuelwood collection work and the intensity of this work. The results show that the age of the household head has a positive and significant ($p < 0.05$) effect on the participation in fuelwood

collection work. This conveys that children in elder households are more likely to be involved in fuelwood collection work by 3%. Such children are expected to increase fuelwood collection intensity by about 18% per week relative to children from young household heads, holding others constant. This result is consistent with the finding of Beyene et al. (2014), who confirmed that children in older household heads increase the probability of participating in fuelwood collection work.

In addition, the education level of the household head has a positive and significant ($p < 0.05$) effect on children's fuelwood collection intensity. The result shows, *ceteris paribus*, children from households with better education levels spend an average of 30% more time gathering fuelwood per week compared to children from lower education household heads. It appears to go against the expectation that better-educated parents have a better understanding of the adverse effect of child labour and hence would not involve their own children in fuelwood collection tasks. This may be explained by the fact that parents with better education are probably involved in government administration and other social issues, suggesting that they may face time constraints in collecting fuelwood and performing other domestic chores. Hence, children living with educated household heads are more likely to participate in fuelwood collection work. This finding is in line with the findings of previous studies (Gebru & Bezu, 2013).

Household size is another predictor variable influencing fuelwood collection work and intensity. The results show that the coefficient of household size has a positive and statistically significant ($p < 0.05$) effect on the intensity of fuelwood collection participation of children. The positive signs of the coefficient of household size suggest that as the number of household members increases by one, children will spend about 16% more time per week on fuelwood collection. This is perhaps explained by the increased quantity and frequency of cooking in a household with large family sizes. In addition, stiffer competition over scarce resources like fuelwood may, in turn, increase child labour in fuelwood collection tasks. This result is consistent with empirical findings conducted in Ethiopia and elsewhere in developing countries (Haile & Haile, 2012; Egeru, 2014; Beyene et al., 2014).

Availability of forests in the community determines the intensity of fuelwood collection by the household, which is measured by the distance a household travels to collect fuelwood from these resources. The results revealed a positive and significant ($p < 0.1$) relationship between distance to the forest and participation and time spent on fuelwood collection. This

implies that as the distance to the forest resources increases, the intensity of fuelwood collection also increases by 6%. Our findings on the effect of distance to the forests on the intensity of fuelwood collection agree with those reported by Beyene et al. (2014) in Ethiopia.

Table 26: Estimated regression results of fuelwood collection intensity and schooling.

Variable	Fuelwood collection participation		Fuelwood collection work hours		School attendance	
	Marginal effects (S.E.)	P> |Z|	Coeff (S.E.)	P > |t|	Marginal effects (S.E.)	P > |Z|
Constant			2.308(0.200) ***	0.001		
Log_Collection intensity (hours)					-0.249 (0.132) **	0.06
Male headship	-0.012 (0.04)	0.764	-0.031(0.22)	0.149	-0.005 (0.054)	0.924
Age of the head	0.031 (0.015) **	0.072	0.177(0.101) **	0.078	0.001 (0.003)	0.82
Years of schooling of the head	0.027 (0.015) **	0.039	0.299(0.112) **	0.085	-0.035(0.018) **	0.05
Household size	0.029 (0.015) **	0.054	0.156(0.098) **	0.022	0.011 (0.029)	0.70
Occupation (farming)	-0.042 (0.039)	0.282	0.025(0.021)	0.332	-0.031 (0.047)	0.51
Number of children	0.008 (0.032)	0.800	0.017(0.027)	0.216	-0.075 (0.045) *	0.095
Log_Household income	-0.069 (0.085)	0.418	-0.015(0.043)	0.477	-0.068 (0.103)	0.51
Log_Distance to forest	0.158 (0.073) **	0.031	0.059 (0.033) *	0.088	0.060 (0.084)	0.47
Female child	0.035 (0.015) **	0.019	0.052(0.018) ***	0.003	0.073 (0.043) *	0.085
Age of child	0.012 (0.01) ***	0.081	0.078(0.039) *	0.083	0.017 (0.008) **	0.042
Birth Order (1st born)						
2nd born	0.080 (0.038) **	0.032	0.037 (0.021) *	0.042	0.058 (0.032) *	0.070
3rd born	0.055 (0.033) *	0.089	0.053 (0.025) **	0.037	0.060(0.023) ***	0.01
4th born	-0.044 (0.067)	0.511	0.022 (0 .031)	0.471	-0.021 (0.085)	0.80
5th born	0.033 (0.082)	0.400	-0.020 (0.037)	0.593	-0.039 (0.096)	0.68
6th born	0.084 (138)	0.610	0.057 (0.060)	0.323	0.029 (0.075)	0.70
Child-to-Family Size Ratio			-0.787(0.083) ***	0.001		
Residuals					0.540 (0.311) *	0.082
No. of observations	603		538		538	
R^2			0.383			

*, ** and *** significant at 10%, 5% and 1%, respectively.

A closer look at the various factors considered in our analysis reveals that variables related to child characteristics play a significant role in determining the probability of a child engaging in fuelwood collection work and the intensity of their participation. As evident from the regression results (column 2), the estimated coefficient of the age of the child has a positive and significant effect ($p < 0.05$) on the likelihood of participating in fuelwood collection work. This suggests that as the child's age increases, so does their probability of

fuelwood collection intensity. Beyene et al. (2014) also concluded that older children are relatively more involved in fuelwood collection, which may result in less time in schooling. Similarly, the sex of the child is another predictor variable with significant ($p < 0.01$) and positive effects on the probability of fuelwood collection work. The positive relationship indicates that female children are more likely than males to participate in fuelwood collection. This implies that the traditional division of labour in sub-Saharan Africa involves a higher work burden on females than males (Nankhuni & Findeis, 2004; Beyene et al., 2014).

5.3.4. Determinants of Children's Fuelwood Collection Work on School Attendance

Colum 3 in Table 26 shows the second stage results of regressing school attendance (binary) on time spent collecting fuelwood using the residuals from the first stage, as shown in Equation 6. Residuals in the school probit model have a positive coefficient and are statistically significant at a 10% level. Thus, the results suggest that the intensity of fuelwood collection is endogenous in the schooling model, which supports the use of IV in our estimation process. The results further revealed that the estimated coefficient of fuelwood collection intensity is negative and significant at a 5% level.

Table 26 (column 3) shows the association between fuelwood collection work and children's school attendance. Participating in fuelwood collection work reduces the likelihood of a child attending school. With a 10% increase in fuelwood collection intensity, the probability of children's school attendance reducing by about 2.5%. In other words, collecting fuelwood for an additional hour per week leads to a decrease of over 2% in the likelihood of attending school. The probable reason is that when environmental resources such as forests are deforested and declined, leading to fuelwood scarcity. Increasing fuelwood scarcity has resulted in long hours of fuelwood collection work spent by school-aged children. This will adversely affect the likelihood of not attending school through the opportunity cost of time spent on fuelwood collection (Gebru & Bezu, 2013). This result is in line with empirical findings in Ethiopia and elsewhere in developing countries (Nankhuni & Findeis, 2004; Ndiritu and Nyangena, 2011; Gebru & Bezu, 2013; Cuesta, 2018) that involving fuelwood collection work negatively affects the likelihood of children's school attendance.

The educational status of the household head affects children's schooling decisions because they belief that education enhances the future earning potential (Haile & Haile, 2012; Woldehanna et al., 2017). Hence, exploring whether fuelwood collection work affects

children's education is vital. Our results show that the estimated coefficient of years of schooling of the household heads has a negative and significant effect on children's school attendance. If the education level of the household head increases by one year, there is a 3.5% probability that the attendance of children in school will decrease. The probable reason is that household heads with some education levels are more likely to be occupied by government administrative issues. According to a study by Haile & Haile (2012), their findings differ from the current research. They found that children of parents with better education tend to work more within the household, negatively affecting their school attendance. Similarly, a study conducted in Tigray, Northern Ethiopia, by Gebru & Bezu (2013) reported that children with educated household heads are about 25% more likely to send their children to school. In the same vein, there is also evidence that children from better-educated parents more often attend school and stay longer in school (Ersado, 2005).

As is common in many developing countries, children are substantially involved in fuelwood collection and other domestic chores. The results indicate that the estimated coefficient of the number of children has a negative and significant ($p < 0.1$) effect on children's school attendance. The result also reveals that an increase in the number of children in the household by one would decrease the likelihood of sending children to school by 7.5%. This is probably because the availability of many children in the household may increase the demand for caretaking, and many school-aged children make the competition over household resources stiffer (Haile & Haile, 2012). This indicates the number of children and investment in child education trade-offs faced by parents; poor households may be constrained to cover their children's school expenses (Gebru & Bezu, 2013). In contrast, a household with many children may provide greater opportunities for school attendance and fewer work hours, especially if there is specialization among family members (O'Brien et al., 2019). Similar studies in Ethiopia show that having more children in a household results in a greater demand for work, decreasing the likelihood of school attendance (Haile & Haile, 2012).

Another predictor variable influencing children's likelihood of school attendance is child age. The results indicate that the estimated coefficient of child age has a positive and significant ($p < 0.01$) effect on children's school attendance. The positive and highly statistically significant coefficient of the child age variable in the schooling probit model shows the probability of school attendance increases by 2%; as the child's age increases by one year, other things remain constant. Interestingly, in the first stage regression, we found that as child age grows, they are more likely to participate in intensive collection work

compared to young children. This result is consistent with the finding of Abafita & Kim (2015) in Tigray that child age had a positive and significant effect on the probability of school attendance. However, this finding is against the finding of Ndiritu and Nyangena (2011) in Kenya that as children grow older and acquire more skills, the opportunity cost of schooling rises and hence less likely to attend school.

Moreover, the child labour literature highlights potential gender-based work participation differentials and their consequent implication on school attendance. Hence, the likelihood of school attendance is investigated from the gender perspective. The results show that the coefficient of child sex is positive and statistically significant ($p < 0.1$), implying that a female child is more likely not to attend school by 7.3% relative to male counterparts. This suggests a gender bias in favour of male children in schooling. A study conducted by Admassie (2002) reported similar findings where being a female child significantly narrows the probability of attending school. However, the results are inconsistent with Gebru & Bezu's (2013) report that gender discrimination in schooling owing to fuelwood collection intensity is not evidenced in Tigray, Northern Ethiopia.

Birth order also has a significant effect on children's school attendance. The results show that the birth order coefficient has a negative and significant ($p < 0.1$) effect on children's school attendance, implying that early births are less likely to attend school. Specifically, children born second and third-order are found to be significantly less likely to attend school. This finding could imply that earlier-born children may have more responsibility for domestic tasks directed to them. A similar result is obtained by Emerson & Souza (2008). On the other hand, household income does not affect fuelwood collection work and children's school attendance in all the estimated models. Thus, there is no evidence that households spend less time collecting fuelwood as their income rises.

5.4. Conclusion and Implications

The study examines the link between fuelwood collection work and children's school attendance using cross-sectional data from the Semien Mountains and adjacent districts of Northwest Ethiopia. This kind of study is important because it helps us understand the linkage between schooling and the natural environment, and it can also make allies of education advocates and proponents of natural resource conservation.

Descriptive statistics indicate that 79% of the sampled children attend school. Besides, the results found that 77% of students were absent from class during the semester. It also showed

that 64% of school-attendant children combined both schooling and fuelwood collection. Similarly, the study's findings revealed that only 23% of school-aged children started grade one at age seven, as the education system in Ethiopia requires. However, around 77% of children of school age were delayed when they first entered grade one. The implication of delaying starting school reduces efficiency and negatively affects children's motivation for schooling. The findings also show that school-age children spent about 7 hours per week collecting fuelwood, including travel and collection time. Increasing fuelwood scarcity has resulted in long hours of fuelwood collection work spent by school-aged children.

The study's main hypothesis is that as fuelwood becomes scarce, households are forced to travel long distances and invest more time and labour in collecting fuelwood, adversely affecting the children's school attendance. Since the decisions to collect fuelwood and school attendance are jointly determined, the bivariate probit model was estimated. The bivariate probit regression results indicate a negative correlation between fuelwood collection work and children's school attendance, suggesting that the two choices are competitive. To address the endogeneity problem, the two-stage conditional maximum likelihood (2SCML) models were used.

The regression results revealed a negative and significant relationship between the ratio of child-to-family size and fuelwood collection intensity, indicating that households with an extra child are likely to reduce the average hour spent gathering fuelwood per week by 79%. It also revealed that children's participation in fuelwood collection work reduces the likelihood of a child attending school by 25%. Similarly, the findings show, holding other things constant, children from households with better education levels spend an average of 30% more time gathering fuelwood per week than children from lower education households. Moreover, the finding reveals that an increase in the number of children in the household by one would decrease the likelihood of sending children to school by 7.5%, suggesting that many school-aged children make stiffer competition over household resources. The findings further revealed that the birth order negatively and significantly affects children's school attendance, implying that early births are less likely to attend school owing to household responsibilities. On the other hand, the results revealed that household income does not affect fuelwood collection work and children's school attendance in all the estimated models. However, there is no evidence that households spend less time collecting fuelwood as their income rises.

The findings of this study have significant implications for educational and environmental policy. They highlight the need to integrate natural resource management programs with primary education programs. Besides, the availability of natural resources, fuelwood, may substantially improve children's school attendance. Thus, it is essential for policies to focus on assisting impoverished households in advancing up the energy ladder, as this can improve children's school attendance. The most practical action would be to increase the availability of improved cookstoves like *Mirt* and access to modern energy. Moreover, the involvement of parents in fuelwood collection work positively contributed to children's school attendance, implying that children's education can be enhanced through changes like a change in cultural attitude towards encouraging parents' participation in fuelwood collection tasks.

CHAPTER SIX: SYNTHESIS

This study explored the link between forest cover change, household energy utilization patterns, and children's school attainment. The study uses spatial data, household surveys, field observations, and key informant interviews. Thus, the chapter synthesis the empirical findings and conclusions that have aimed to link forest cover change, household energy utilization patterns, adoption of improved cookstoves, and children's human capital development participated in fuelwood collection activities. It also presents the implications of the study findings and suggestions for future research. Finally, the synthesis provides the research contribution in terms of empirical and methodological.

6.1. Introduction

Forests are the major sources of energy in many developing countries, and increasing the needs of the growing population affects the forest cover and use patterns. Although forest cover and energy use patterns are the pillars of Ethiopia's Climate Resilient Green Economy Strategy, there is a limitation in empirical studies that substantiate the link. Forest cover and energy use patterns have some linkage. For example, fuelwood production and consumption technologies are generally rudimentary and inefficient, leading to deforestation and affecting the energy supply (Article 1). The scarcity of appropriate energy sources has led poor households to spend considerable time collecting fuelwood, which could have been spent on more productive activities (Article 4). The extensive need for energy, which leads to the widespread cutting of trees, is also becoming another threat to the remaining forest in the country. With unprecedented rates of deforestation, fuelwood scarcity is inevitable. In turn, this situation has impinged on household livelihoods in various ways. As a result, many people encountered increasing difficulty obtaining sufficient fuelwood supplies for domestic use.

Besides, fuelwood collection can potentially contribute to deforestation, leading to fuelwood scarcity. Fuelwood collection often has greater impacts on the welfare of women and children since they are traditionally responsible for fuelwood collection. When fuelwood becomes scarce, households are expected to use a substitute or complementary alternatives. Households may switch to commercial energy alternatives if available. Rural households may cope with fuelwood scarcity by shifting from state forests to private tree cultivation. Thus, initiatives that improve dwelling energy end-use efficiency by reducing deforestation

and fuelwood collection intensity are expected to enhance environmental sustainability, household welfare, and children's school attendance.

Therefore, it is frequently suggested that initiatives intended to promote the transition to clean energy should be encouraged. Different policy instruments, such as information campaigns advocating improved and more efficient biomass stoves or subsidy schemes to cover the expenses of low-income people for adopting new technology to stimulate a fuel-switching process and improve household livelihoods as well as children's school attendance. Such a transition is crucial where fuelwood is vital domestic fuel, and forest degradation is a severe problem. However, these efforts do not deter households from collecting fuelwood from forests, possibly due to limited fuelwood collection options or weak enforcement of forest regulations, especially on planted forests. Thus, this thesis addressed forest cover changes, household energy utilization patterns and children's school attendance.

6.2. Forest Cover Dynamics

Forests are vital for the welfare of millions of people in Ethiopia. The reliance of poor people on forests for survival leads to forest depletion and exacerbates environmental stress. Assessing forest cover change patterns and drivers is important for sustainable forest management, especially in developing countries encountering severe deforestation and forest degradation. Increased availability of remotely sensed data provides an opportunity to analyze historical and current forest cover change patterns. Chapter two provides an approach that can help to improve understanding of forest cover changes and their drivers for heterogeneous landscapes of the afro-alpine Semien Mountains. People-forest interaction is determined by the interaction in space and over time of biophysical and human factors. A study of such interaction needs to conceptualize the relationship between the driving forces of human-induced changes, the processes and activities among them, and human behaviour and organizations.

Forest decline is identified as an important problem in Ethiopia and the study area. However, relevant data are scarce, the existing knowledge is incomplete, and interpretation is largely influenced by the prevailing environmental crises. The existing few studies tend to emphasize the rate of decline rather than the causative processes. Hence, it is vital to address this challenge, particularly the complexity of the causative links in time and space. A complete understanding of forest cover change requires determining the magnitude and

characteristics with consistent estimation methods. The study area is a part of the Afroalpine Center of Plant Diversity in Ethiopia and embraces a considerable diversity in topography, vegetation types, soils and climates. Historically, the area has been influenced by early settlement and agricultural history, which have influenced the forest use patterns.

Four sets of satellite imagery, including Landsat 4–5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI), of 1984, 1996, 2008, and 2020, respectively, were employed to assess forest cover changes. Between 1984 and 2020, a sharp reduction in forest resources and increased agricultural land were demonstrated (Table 7 and Figure 7 in Article 1). The sharp reduction in forest cover can mainly be attributed to changes in government and policies. This change contributed considerably to cutting trees from natural forests to fulfil the growing population's domestic energy needs and food demand. In addition, war, drought and famine in this period contributed to deforestation and forest degradation. This change inevitably has a far-reaching consequence on the availability of forest ecosystem services, like fuelwood (Article 1). Faced with such a precarious situation, only a guided forest conservation policy which gradually applies proper sensitization, participatory forest mapping and incorporation of forest communities in the sustainable management of forest resources can be long-lasting. The study concludes that forest cover change must be seen as part of broader socio-economic, demographic, institutional, and environmental factors. It is also argued that future development interventions should focus on collaborative efforts among stakeholders to promote participatory forest management and initiatives that encourage the transition to cleaner and more fuel-efficient energy sources (Article 3). Any policy intervention that adopts demand sid strategies (e.g., improved biomass cookstoves) should prioritise the relatively forest-degraded areas of the Semien Mountains to reduce fuelwood consumption. Moreover, specific forest policies on increasing forest stock will be more effective if it considers the population pressure of the study area.

6.3. Household Energy Utilization Patterns

Energy, one of the imperative needs of human beings, plays a vital role in socio-economic development. The study argued that exploring household energy utilization patterns and identifying factors determining household cooking fuel choices provide valuable insights to design effective policies to engender sustainable energy use and reduce over-reliance on the already depleted forest resources for biomass energy (Article 2). Ethiopia is among the few countries with a broad diversity of abundant renewable energy resources. Paradoxically, the

country suffers acute deficits in terms of access to clean and modern energy. National statistics indicate that the potential of biomass energy is being exploited, representing nearly 50% of the woody biomass potential and 30% of agricultural residue, but only 5% of hydroelectric potential and less than 1% of combined wind, solar and geothermal potential is currently exploited (Guta, 2014a). The country has also experienced unprecedented growth in demand for electricity.

One of the most urgent problems in Ethiopia is cooking with biomass fuels by a large part of the population. Such energy consumption pattern is also linked to deforestation and forest degradation (Article 1), suggesting that biomass fuel use significantly erodes local, regional and global environmental sustainability. The household sector consumes the greatest proportion of total energy across the globe. In Ethiopia, the household sector account for about 88% of the total energy consumption. Baking *injera* alone takes up to 60% of the total energy use (Article 2).

A household residing in the study area does not rely on a single energy source; instead, multiple fuel sources are utilized. In addition to fuelwood, a household may choose dung, charcoal, crop residue, and electricity. Some of these energy sources can be used as complements with another source, while others may be used as substitutes (Article 2). As a result, there is evidence of fuel stacking as households do not abandon fuelwood as they adopt other energy sources like electricity. The study shows that households' energy utilization pattern is skewed towards biomass fuels, particularly fuelwood. The results also showed that fuelwoods are not inferior, as opposed to the energy-ladder hypothesis, and households continue to rely mainly on these fuels for cooking. However, although fuelwood is a renewable fuel source, over-extraction can lead to environmental degradation and thus can significantly negatively impact sustainable development (Article 2). The study revealed that households choose multiple fuels for domestic chores for various reasons, including that entire reliance on single energy may be subject to price fluctuations and unreliable supply. Thus, households tend to follow a multiple fuel use strategy as their income, education, and settlement patterns improve. We also have evidence of fuel stacking, as there is an increase in the number of fuel types used by households as socio-economic status improves. Over time, a tendency to shift from traditional to mixed fuels is also observed. The study concluded that improvement in income and non-income factors enhanced the likelihood that a household would use electricity and fuel-efficient cooking technologies, suggesting a reduction in strain on local forest resources (Article 3).

6.4. Performance and Adoption of Improved Cookstoves

The concept of energy efficiency and hence the development of new and energy-efficient stove technologies has its origin in the oil price shocks of the 1970s (Kumar et al., 2017). Since then, improved cookstoves have been regarded as a technological substitute for fuelwood scarcity (Amacher et al., 1999). However, knowledge about the characteristics of stove adoption is sparse. Although improved stoves have been introduced in Ethiopia since the late 1980s, much of the evidence has focused on a description of the benefits in the area of health (Gebreegziabher, 2007). Various government and non-governmental organizations are trying to address deforestation and forest degradation by introducing and disseminating various fuel-saving technologies. Although studies have shown that these stoves use less fuel and can, thus, be assumed to result in less innocuous health effects, these technologies have not been universally adopted in Ethiopia. Besides, in Ethiopia as well as the study area, empirical evidence on the effectiveness or fuel-saving efficiency of improved cookstoves, particularly wood stoves, is scanty. The third article of the thesis analyses improved cookstoves' performance and determines factors that affect stove adoption behaviour. This enables us to understand the main factors determining the adoption of *Mirt*-improved stoves and provide a solid evidence base for developing policies and practical solutions to achieve clean cooking in the study area and elsewhere in Ethiopia.

The KPT results showed that the use of Mirt-improved cookstoves reduced the amount of fuelwood used at a household level significantly as compared to the use of three-sone stoves, suggesting that the *Mirt* stove saves about 5.4 kg of fuelwood/*injera* baking session (Table 21 and Fig. 15). Similarly, the KPT analysis revealed variations in *injera* baking duration, which was longer when a three-stone stove was employed (Table 21 and & Fig. 16 Article 3). This conveys that *Mirt*-improved cookstoves have the potential to narrow the gap between energy demand and supply through their increased efficiency and consequent enhancement of biomass fuel availability. Thus, substituting three-stone stoves with Mirt-improved cookstoves is recommended to improve the forest resources and children's school participation and reduce fuelwood collection frequency. Moreover, the finding revealed that various socioeconomic, environmental and institutional factors determine the adoption of improved biomass cookstoves. The results show that education positively and significantly determines Mirt stove adoption. The findings further show that the probability of adoption of Mirt stove will increase for households with separate kitchen facilities.

Significant biomass fuel use efficiency improvements can be achieved by substituting the traditional three-stone stove with Mirt-improved cookstoves (Negash et al., 2021). For instance, the conversion of 14.44 million rural and urban households to *Mirt* stoves is estimated to have resulted in an annual fuelwood saving of about 7,778,800 tons per year, which is equivalent to 137,192.24 ha of forest cover decline (Damte & Koch, 2011). According to the study, Mirt stoves lessened the strain on forests and the time and effort required for women and children to collect fuelwood, as well as allowing for increased school attendance and reduced opportunity costs. Hence, promoting fuel-efficient stoves will produce remarkable socio-economic improvement and environmental recovery. However, large investments from both the public and private sectors need to be encouraged. While designing new ICS interventions, the demand and supply side drivers should be carefully identified and considered.

6.5. Fuelwood Collection and Children's School Attendance

Deteriorating environmental resources, particularly forests, increases the costs of collecting environmental products such as fuelwood. Fuelwood collection is part of the daily routine of many households in Ethiopia. Most of the collection burden falls on children and women, particularly school-age children, diverting their time from education. This type of child labour frequently leads to foregone schooling, which might impact their future human capital development. While several factors might affect children's school attendance at the primary level, the question of how important children's fuelwood collection participation was in determining whether or not they attended school and attained desired progress (Article 4).

The central tent of this study was to test whether children's school attendance in primary school was inversely affected by fuelwood collection works. It enables us to understand the link between fuelwood collection participation and school attendance and recommend policy actions to improve the education sector and environmental conservation. The study found that many school-age children involved in fuelwood collection face problems in their education, mainly school absenteeism (Fig. 18). Participating in fuelwood collection work reduces the likelihood of a child attending school. With a 10% increase in fuelwood collection intensity, the probability of children's school attendance reducing by about 2.5% (Table 26). The probable reason is that when environmental resources such as forests are deforested and declined, leading to fuelwood scarcity (Article 1). Increasing fuelwood scarcity has resulted in long hours of fuelwood collection work spent by school-aged

children. This will adversely affect the likelihood of attending school through the opportunity cost of time spent on fuelwood collection (Article 4).

The implication of this study is potentially important from an educational policy perspective and argues for integrating local natural resources enhancement programs with the education program. Thus, the study concluded that deforestation and forest degradation limit a household's access to forests, which may negatively impact human capital formation and, consequently, an individual's potential earnings when getting older. The finding confirms previous studies highlighting the adverse effects of fuelwood collection on children's schooling. Besides, policy should focus on supporting poor households relying heavily on fuelwood to progress the energy transition to improve children's school attendance. Moreover, promoting fuel-efficient cookstoves may reduce the frequency of fuelwood collection and deforestation and improve children's school attendance.

6.6. Policy Implications and Future Research Directions

6.6.1. Policy Implications

Based on the findings of the study, the following recommendations are suggested.

- Forests provide vital goods and services for the well-being of human beings. However, these resources are being degraded by the escalating needs of the growing population. The continued loss of forest cover threats the endangered endemic species and availability of forest products. Thus, site-specific community-based awareness creation about the appropriate use of forests and other resources and the conservation and rehabilitation of the environment are compelling. Besides, policy attention should focus on making local communities aware of the co-existence of nature conservation and sustaining their livelihood. Further, information about changing patterns of forest coverage and its drivers can be used as inputs for modelling future changes and informed decisions making during policy formulation.
- Wider adoption of an agro-forestry system, expansions of community wood lots and plantations, increasing the productivity of forest resources, and replacing open access areas with fast-growing biomass plantation trees like *Acacia decurrens* are policy options to fulfil the growing biomass stock as a potential supply.
- Considering that most of the population in the study area relies on fuelwood for cooking, it would be beneficial for the government to prioritize social forestry

initiatives such as tree planting and afforestation. These activities can help address the issue of fuelwood scarcity and promote an increase in forest cover.

- Forest cover change and biomass availability should be monitored over time, particularly in areas characterized by rapid forest cover change and high rates of population growth. Better information about the type, quantity and quality of biomass fuels is needed to comprehensively understand the individual and social costs of forest cover change concerning welfare outcomes for the people living in these rapidly changing landscapes.
- Given the finding that income is a significant driver, household energy choices and transition in the context of the study area are also influenced by several non-income and context-specific factors. This means that the success of energy transition towards clean and modern fuels depends not only on household income but also access to road, market, cost of technology, socio-cultural setting and location-related variables. Thus, policymakers and energy planners need to consider the influence of non-income factors when designing energy policies.
- As shown in the study findings, education has positive returns on people's energy choice behaviour. Therefore, improving education and raising public awareness of the adverse effects of an overreliance on biomass on both the environment and human health is recommended. Improving awareness can influence behavioural patterns and engender the transition from traditional to modern fuels.
- Improving biomass fuel use efficiency has the potential to mitigate the adverse socio-economic, health and environmental impacts associated with traditional biomass fuel use. In addition, improved stoves have the potential to save fuel and time, significantly contributing to the mitigation of GHG emissions. Hence, the development of improved biomass technology will be instrumental in the energy mix. Specifically, *Mirt* stoves for baking *injera* are vital for alleviating fuelwood collection intensity, deforestation and indoor air pollution. Therefore, to create and implement better stove technology for clean cooking, energy planners and policymakers need to consider the key factors, such as revitalizing the supply chain through market development to encourage the adoption of improved stoves.
- Promoting fuel-saving technologies for domestic cooking can have important welfare implications for children’s human capital development since fuelwood collection disproportionately affects school-age children. Thus, policymakers should focus on awareness creation that can articulate the benefits of fuel-efficient stoves, including

reducing fuelwood collection frequency, improving school participation and saving forest resources.

- Last but not least, results support the hypothesis of a negative association between deforestation and children's school attainment. This means that deforestation may contribute to the low educational status of children in the study area by increasing the burden of fuelwood collection work on children. The lower likelihood of school attendance with additional work hours allocated to fuelwood collection activities suggests that parents trade off investment in children's education in favour of using children for labour. Hence, specific policies and programs must be designed to target children suffering from the hardship of fuelwood collection. Current fuel-gathering practice in the study area indicates the direct involvement of children with increasingly low school participation, which must be addressed as a high-priority energy development agenda.

6.6.2. Future Research Directions

Various issues were raised and discussed in different chapters of this research work. A lot remains, however, to be done in this area. Therefore, based on the findings of this study, further investigations are suggested in the following areas.

- Research on addressing the dwindling forest cover of the Semien Mountains through buffer plantations with energy crops.
- Estimating the impact of forest cover changes on the forest ecosystem service values and the socio-economic well-being of adjacent communities.
- Nowadays, a variety of improved stoves come out from different stakeholders. However, studies are limited on testing protocols, real thermal efficiency and pollutant emission in the field. Hence, it is necessary to investigate the stove performance in the real household kitchen in future studies.
- In addition, it is strongly felt that studies focusing on the factors affecting the uptake and sustainable use of fuel-efficient stoves in Ethiopia are still limited. Although some enablers and barriers were identified, it is hard to answer which is the most significant factor to be paid attention to. Hence, the temporal and spatial variances in potential factors and their impact should be considered in future studies.

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Annex

Addis Ababa University

College of Development Studies

Center for Environment and Development Studies

Household Survey Questionnaire

Dear respondents, my name is Belete Debebe.

I am a PhD student at Addis Ababa University, College of Development Studies. I am undertaking a research project entitled "**Forest Cover Changes and Household Energy Utilization Patterns in the Semein Mountains and Adjacent Districts, Northwest Ethiopia**".

The main objective of this questionnaire is to generate primary data on the demographic and socio-economic characteristics of the household, forest cover change, household energy utilization patterns, including stove-related information as well as school participation and resource collection by children, which will be used to fulfil an academic requirement for the Degree of Doctor of Philosophy in Environment and Development.

Therefore, your kind cooperation and active participation with genuine responses during the data collection will be vital for the overall success of the study. Results and any other details will not be used for an unintended purpose. To this end, the anonymity of the respondents and the confidentiality of the responses will be confidentially protected.

Lastly, I thank you for your cooperation!

Household Identification and Interview Summary (to be filled by data collector)	
Name of the study Woredas	
Name of the study Kebele	
Household identification code	
Name of the respondent	
Sex of the respondent	
Relationship to the household head	
Interviewer name	
Date of the interview	
Time of the interview	Starting time:
	Ending time:

Part 1: Household Socio-economic and Demographic Profile

<table>
<tr><th>S. No</th><th>Questions</th><th>Possible answer</th></tr>
<tr><td>1</td><td>What is the sex of the household head?</td><td>1. Male-headed
2. Female-headed</td></tr>
<tr><td>2</td><td>Age of the household head?</td><td>Age in completed years _____</td></tr>
<tr><td>3</td><td>Marital status of the household head?</td><td>1. Single
2. Married
3. Divorced/ separated
4. Widowed</td></tr>
<tr><td>4</td><td>Can you read and write?</td><td>1. Yes
2. No</td></tr>
<tr><td>5</td><td>If Yes, what is the highest-grade level you have completed?</td><td>Write the grade level _____</td></tr>
<tr><td>6</td><td>What is the size of your household, including yourself, by age and sex?</td><td>
<table>
<tr><td>Age</td><td>Male</td><td>Female</td><td>Total</td></tr>
<tr><td>Under-5 years</td><td></td><td></td><td></td></tr>
<tr><td>6-14 years</td><td></td><td></td><td></td></tr>
<tr><td>15-64 years</td><td></td><td></td><td></td></tr>
<tr><td>65 + years</td><td></td><td></td><td></td></tr>
</table>
</td></tr>
<tr><td>7</td><td>What are the means of livelihood for the household?
(multiple responses possible)</td><td>1. Crop production
2. Livestock production
3. Mixed farming
4. Petty trade
5. Wage labour
6. Government
7. Others (specify) _____</td></tr>
</table>

Part 2: Membership to community organization

<table>
<tr><td>8</td><td>Are you a member of any local social organization group within your locality?</td><td>
<table>
<tr><th>Membership in community org'n</th><th>Yes</th><th>No</th></tr>
<tr><td>Farmers' association</td><td></td><td></td></tr>
<tr><td>Credit group (Edir or equb)</td><td></td><td></td></tr>
<tr><td>Religious group</td><td></td><td></td></tr>
<tr><td>School Committee</td><td></td><td></td></tr>
<tr><td>Women's group</td><td></td><td></td></tr>
<tr><td>Forest user's group</td><td></td><td></td></tr>
<tr><td>Others (specify)</td><td></td><td></td></tr>
</table>
</td></tr>
</table>

9	In the 12 months, how many days did you participate in the meeting?	_____ (number of days)
10	Do you exchange information on fuel-saving cooking stoves by belonging to these organisations?	1. Yes 2. No
11	Do you think membership in these community organisations influences you to adopt improved cooking stoves?	1. Yes 2. No

Part 3: Housing Unit Information

12	What materials have been used to construct the wall of the housing unit?	1. Wood and mud 2. Wood only 3. Stone and mud 4. Others (specify)_____
13	What materials have been used to construct the roof of the housing unit?	1. Corrugated iron sheet 2. Thatch grass 3. Plastic/Shera 4. Others (specify)_____
14	How many rooms are in the housing unit?	_____ (number of rooms)
15	Do you have a separate room that is used as a kitchen?	1. Yes 2. No
16	How many windows does the kitchen have?	_____
17	What is the major source of drinking water for the household?	1. River/stream 2. Protected well/spring 3. Unprotected well/spring 4. Private hand-dug well 5. Public hand-dug well 6. Other (specify) _____
18	Where is the water source located?	1. In own dwelling 2. Elsewhere
19	If the water source is located elsewhere, how long does it take you to fetch water for household use (round trip)?	_____ hours/minutes
20	How often does the household fetch water in a day?	_____ (number of times)
21	Compared to 5 years ago, how do you perceive the current water availability in your locality?	1. More available 2. Less available 3. The same 4. Do not know
22	How long (in hours/minutes walking) is this household from the nearest primary school?	_____ hours/minutes

23	How long (in hours/minutes walking) is this household from the extension worker?	_____ hours/minutes
24	How far is this household from the main road?	_____ hours/minutes
25	How far is this household from the local market?	_____ hours/minutes
26	Do you have access to electricity in your home?	1. Yes 2. No

Part 4: Land ownership

27	Does the household own land for cultivation?	1. Yes 2. No
28	What is your household's total size of landholding?	_____ timad/hectare
29	Have you planted any trees on your farmland?	1. Yes 2. No
30	If **No**, what is the factor limiting you to plant trees? *(multiple responses possible)*	1. Shortage of land 2. Lack of motivation 3. Lack of land-use certificate 4. Labour shortage 5. Others (specify) _____
31	If you plant trees, when did you start?	_____ years
32	If you plant trees, specify the total number of trees you planted in the last three years.	_____ number of trees
33	What are the main purposes of tree planting? *(Rank according to importance)*	**Purpose of tree planting** / **Rank** For domestic fuelwood use Fuelwood for sale Timber/poles for sale To increase the value of land Others (specify)
34	Do you have a land-use certificate?	1. Yes 2. No
35	If **Yes**, do you think the land-use certificate triggered you to plant trees?	1. Yes 2. No
36	If **No**, do you think a lack of land use-certificate affects you to plant trees?	1. Yes 2. No
37	Have you ever received any training from the woreda/ kebele development agent on tree plantation and forest protection?	1. Yes 2. No

Part 5: Livestock ownership

38	How many of the following livestock does the household currently own?	Type of livestock	Currently available	Type of livestock	Currently available
		Cow		Horse	
		Oxen		Donkey	
		Calves		Mule	
		Heifer		Poultry	
		Sheep		Others	
		Goat			
39	How many did you earn (in birr) in the last 12 months if you sold?	_____ birr			
40	If the household owns any of the livestock, where do you graze? *(multiple responses possible)*	1. Communal grazing land 2. Private grazing land 3. Purchase			

Part 6: Access to Credit Services

41	Did you have access to credit services in the last 12 months?	1. Yes 2. No
42	If **Yes**, what is the source of credit?	1. Money lender/Arata 2. Friends/neighbours 3. Family members 4. Credit and Saving Institution 5. Other, specify_____

Part 7: Household Expenditure

43	**Food expenditure and consumption that was bought**		
	Food type	Estimated expenditure per month (Birr)	Estimated total expenditure per year
43.1	**Cereals**		
	Teff		
	Barley		
	Wheat		
	Sorghum		
	Maize		
43.2	**Pulses**		
	Lentils		
	Horse Beans		
	Chick Peas		
	Cow Peas		

43.3	**Vegetables**		
	Onion		
	Tomato		
43.4	**Others**		
	Oil		
	Salt		
	Sugar		
	Pepper		
	Coffee		
	Tea		

44. Non-Food Expenditure

	Items	Estimated expenditure per month (Birr)	Estimated total expenditure per year
44.1	**Clothing expenses**		
	Clothing (dressing and footwear) for parents		
	Clothing (dressing and footwear) for children		
44.2	**Educational expenses**		
	Exercise books, pens, pencils, uniforms, etc.		
44.3	**Health expenses**		
	Modern medical treatment and medicines		
	Traditional medicine and healers		
	Health insurance		
44.4	**Fuel expenses**		
	Fuelwood		
	Dung cake		
	Kerosene		
44.5	**Religious and other cultural expenses**		
44.6	**Marriage ceremony**		
44.7	**Others**		
	Soap for cloths		

Part 8: Forest Cover and related information

45	For how many years did you live in this area?	_____ years
46	Since living in this area, have you noticed any population change?	1. Yes 2. No
47	If **Yes**, what do you think about the cause of population change?	1. High Fertility 2. In-migration 3. Both
48	What type of forests exists around your area? *(multiple responses possible)*	1. State Forest 2. Community forest 3. Private forest 4. Others (specify) _____
49	Do you agree that the forest resources of SMNP are an important source of livelihood for the household?	1. Yes 2. No
50	Can you or any family member harvest the following forest products from SMNP? *(multiple responses possible)*	1. Fuelwood 2. Fodder/Grass 3. Housing construction material 4. Medicinal plants 5. Others (specify) _____
51	What benefits do you obtain living in and around the SMNP forest resources? *(multiple responses possible)*	1. None 2. Fuelwood 3. Construction materials 4. Medicinal plants 5. Grazing land 6. Others (specify) _____
52	What kind of **problems** do you face because of living in and around the SMNP? *(multiple responses possible)*	1. Crop damage by Gelada Baboon 2. Livestock predation 3. Restriction to access Fuelwood 4. Restriction to access fodder for livestock 5. Restriction to expand farmland 6. Others (specify) _____
53	Have you noticed any changes in and around the SMNP forest resources?	1. Yes 2. No
54	If **Yes**, how do you assess the changes in the forest cover of the SMNP?	1. Decrease 2. Increase 3. Not realising the change
55	If the forest cover is decreased, what are the reasons?	1. Population growth 2. Forest fire 3. Harvesting fuelwood 4. Agricultural expansion 5. Weak institutions

		6. Others (specify) _____
56	If the forest cover is increased, what are the reasons?	1. Improved awareness about the forest 2. Better enforcement of laws 3. Better institutions 4. Improved sense of ownership 5. Tree plantation program 6. Others (specify) _____

Part 9: Energy Sources and Consumption Pattern

57 Which fuel type does your household use most for the following tasks?

57.1 Type of fuel *(tick all that apply)*	**57.2 End uses**			
	57.2.1 Type of fuels the HH use for baking/injera or bread. (✓)	57.2.2 Type of fuels the HH used for cooking stew/wet, making coffee or tea, etc. (✓)	57.2.3 Type of fuels the HH use for indoor lighting (✓)	57.2.4 Type of fuels the HH use for room heating (✓)
1. Electricity				
2. Fuelwood				
3. Charcoal				
4. Dung cake				
5. Crop residues				
6. Branches, leaves and twigs				
7. Kerosene				
8. Solar energy				
9. Batteries				
10. Biogas				
11. Others (specify)				

58 What are the most preferred fuel choices for household cooking/baking?

(rank from the most preferred to the least)

Type of fuels	Baking fuels	Cooking fuels
Fuelwood		
Charcoal		
Dung cake		
Crop residues		
Branches, leaves and twigs		
Others (specify) _____		

59	What is the reason for the use of these fuels?	1. Available 2. Affordable 3. Easy to use 4. Personal preference 5. Others (specify) _____
60	How often do you use these fuels?	1. Regularly 2. Sometimes 3. Never use
61	What is the factor influencing household fuel choice? *(multiple responses possible)*	1. Fuel price 2. Availability in the locality 3. Accessibility 4. Convenience 5. Others (specify) _____
62	Do you face fuel scarcity in your locality?	1. Yes 2. No
63	If Yes, how does the household acquire fuel?	1. Purchasing 2. Collecting 3. Both
64	What kinds of fuel are available for purchase in the local market if you purchase? *(multiple responses possible)*	1. Fuelwood 2. Dung 3. Crop residue 4. Kerosene 5. Charcoal 6. Others (specify) _____
65	If you purchase, how long do you travel to purchase this fuel?	_____minutes
66	How much money did you spend on fuel purchases in the last month?	_____ Birr/months
67	Compared to 5 years ago, how do you assess the current fuel price?	1. Increase 2. Decrease 3. The same
68	If you get fuel by collection, what do you collect?	1. Fuelwood 2. Dung 3. Branches, leaves and twigs 4. Crop residues
69	Where do you collect the fuelwood? *(multiple responses possible)*	1. Community-owned forest 2. Naturally grown trees on farmlands 3. Privately grown trees 4. Others (specify) _____
70	Where do you get the dung cake? *(multiple responses possible)*	1. Communal grazing land 2. Own livestock 3. Purchasing 4. Others (specify) _____

71	Who participates in the collection? *(multiple responses possible)*	1. Mother 2. Father 3. Male child 4. Female child
72	How often do you collect fuelwood per week?	_____ number of days in a week
73	How long does it take to get fuelwood? (round trip)	_____minutes
74	Compared to 5 years ago, how is the current fuelwood collection difficulty?	1. Less difficult 2. Moderately difficult 3. Very difficult to find
75	Have you encountered any problems during fuelwood collection?	1. Yes 2. No
76	If **Yes**, what kind of problems are faced during fuelwood collection? *(multiple responses possible)*	1. Harassment by people 2. Physical injury 3. Bitten by snake and insect 4. Others (specify)_____
77	How do you transport the fuelwood?	1. Human labour 2. Donkey 3. Cart 4. Others (specify)_____
78	Which time of the year do you face fuelwood scarcity?	1. Dry season 2. Cold/rainy season
79	Do you or any household member travel a long distance to collect fuelwood?	1. Yes 2. No
80	If Yes, compared to 5 years ago, how do you perceive the current distance travelled for collecting fuelwood?	1. Increased 2. Decreased 3. No change
81	Compared to 5 years ago, how do you assess the current availability of fuelwood in your locality?	1. Increased 2. Decreased 3. No change
82	If increasing the current fuelwood availability, what are the reasons?	1. Increasing household tree plantation 2. Increasing the number of fuelwood sellers 3. Availability of fuelwood substation 4. Others (specify)_____
83	If decreasing the current fuelwood availability, what are the reasons?	1. Increasing demand for fuelwood consumption 2. Increasing demand for fencing and construction 3. Decline in local forest resources 4. Others (specify)_____
84	How many kgs of fuelwood on average does the household use weekly?	_____ kg

<table>
<tr><td>85</td><td>What are the most preferred coping mechanisms of the household in case of a scarcity of fuelwood supplies?

(multiple responses possible)</td><td>
<table>
<tr><th></th><th>Coping mechanisms to fuel shortage</th><th>Rank</th></tr>
<tr><td>1</td><td>Spend more time on the fuelwood collection</td><td></td></tr>
<tr><td>2</td><td>Reduce cooking</td><td></td></tr>
<tr><td>3</td><td>Shift to traditional sources.</td><td></td></tr>
<tr><td>4</td><td>Buy from the market.</td><td></td></tr>
<tr><td>5</td><td>Use of improved cooking stoves</td><td></td></tr>
<tr><td>6</td><td>Asking relatives</td><td></td></tr>
<tr><td>7</td><td>Others (specify)_____</td><td></td></tr>
</table>
</td></tr>
<tr><td>86</td><td>Do you plant trees for fuelwood?</td><td>1. Yes 2. No</td></tr>
<tr><td>87</td><td>Do you mix biomass fuels for domestic use?</td><td>1. Yes 2. No</td></tr>
<tr><td>88</td><td>If Yes, what combination of fuel sources do you mix for baking/cooking?

(multiple responses possible)</td><td>1. Fuelwood with dung
2. Fuelwood with crop residue
3. Fuelwood with dung and crop residue
4. Fuelwood with dung, crop residue, & charcoal
5. Dung with crop residue
6. Dung with crop residue and charcoal
7. Others (specify)_____</td></tr>
<tr><td>89</td><td>If Yes, what is the reason for the fuel mix?

(multiple responses possible)</td><td>1. To save fuelwood
2. Do not have enough dung
3. Do not have enough wood
4. It is a culture
5. Others (specify) _____</td></tr>
<tr><td>90</td><td>Do you have access to an alternative energy source (s)?</td><td>1. Yes
2. No</td></tr>
<tr><td>91</td><td>If Yes, what are the alternative energy sources the household use?</td><td>1. Biogas
2. Solar energy
3. Wind power
4. Others (specify)</td></tr>
</table>

Part 10: Stove-Related Information

92	Where do you usually cook?	1. Inside the house 2. In a separate kitchen 3. Outside
93	Who does most of the cooking in the household?	1. Wife 2. Daughter 3. Others (specify)_____
94	How old is the age of the main cook?	_____ years
95	Educational status of the main cook?	_____

96	How many times do you bake injera per week?	_____ days
97	How many times do you cook (other than injera) per day?	_____ days
98	What type of cooking stoves do you use?	Types of stove / Baking / Cooking Three stone fire Improved biomass cooking stove Others (specify)_____
99	Do you know the problems associated with three-stone fires?	1. Yes 2. No
100	If **Yes**, what are the problems associated with the three-stone fire stove? *(multiple responses possible)*	1. Itching of the eyes caused by smoke 2. Burning from flames 3. Dirty kitchen caused by ashes 4. Respiratory diseases due to smoking 5. Increased rate of deforestation 6. Others (specify)_____
101	Have you heard about improved cooking stoves?	1. Yes 2. No
102	If **Yes**, where did you get the information from? *(multiple responses possible)*	1. NGO working in the study area 2. Development workers 3. Neighbours/friends 4. Manufacturer/producer 5. Mass Media (Radio, TV) 6. Others (specify)_____
103	Do you own an improved biomass cooking stove?	1. Yes 2. No
104	If you do not have an improved biomass cooking stove, why? *(multiple responses possible)*	1. Expensive 2. Unavailability 3. Don't want to change traditional practice 4. Lack of information 5. Don't know its use 6. Others (specify)_____
105	If you own, which type of improved biomass stoves do you own? *(tick all that apply)*	Types of improved stove / Baking / Cooking Lakech Mirt Gonzie Others (specify)
106	How long have you been adopting an improved Mirt cooking stove?	_____years
107	Which fuel type do you use most for Mirt biomass stove? *(multiple responses possible)*	1. Fuelwood 2. Dung 3. Crop residues 4. Branches, leaves, and twigs
108	What is the usage rate if you use the improved Mirt biomass cooking stoves?	1. Regularly 2. Sometimes 3. Never use

109	How did you **get** the improved Mirt biomass cooking stove?	1. Purchase 2. Supplied by NGO for demonstration 3. Others (specify) _____
110	If you **purchased** the Mirt stove, from where did you buy it?	1. Market 2. Local producer 3. Others (specify) _____
111	Who decided to buy the improved Mirt stove?	1. Husband 2. Wife 3. Together
112	What is the main factor that inspires your decision to buy the Mirt stove? *(multiple responses)*	1. Speed of cooking 2. Fuel efficiency 3. Affordable 4. Less smoke 5. Others (specify)_____
113	Are there producers of improved Mirt cooking stoves in your kebele?	1. Yes 2. No
114	If **No**, how long do you travel to get the improved stove to the market/producer?	_____ hours
115	Does the distance you travel to the producer/market affect you to adopt the Mirt cooking stove?	1. Yes 2. No
116	Have you got any training on an energy-saving device by the Woreda/kebele energy expert?	1. Yes 2. No
117	If **Yes**, what type of training have you got?	1. Biogas technology 2. Improved biomass Mirt stove 3. Solar energy 4. Others (specify)_____
118	How much did you pay for the improved Mirt biomass cookstove?	_____ birr
119	What would you say about the price of an improved Mirt biomass cooking stove?	1. Cheap 2. Fair 3. Expensive
120	Do you believe using the Mirt stoves saves you or other household members' time?	1. Yes 2. No
121	If time is being saved, how is it used?	1. Give more time to children's care 2. start income generating activities 3. Able to attend a community meeting 4. Others (specify) _____
122	Compared to the traditional stove, the improved stove reduces the **number of times** you go to collect fuel each week.	1. Yes 2. No
123	How many times per week did you collect fuel for the traditional stove?	_____
124	How many times per week do you collect fuel after using the Mirt stove?	_____
125	Compared to the three-stone fire, how do you assess the **time spent on baking** injera with the Mirt stoves?	1. Reduced 2. Increased 3. Remain the same

126	Do you think the Mirt stove saved more fuel than the three-stone fire?	1. Yes 2. No
127	If **Yes**, how do you perceive fuel saving?	1. Collecting fuel less often 2. Spend less money on fuel 3. Others (specify) _____
128	Compared to the traditional stove, the Mirt stove produces:	1. Less smoke 2. More smoke 3. The same
129	Do you think the improved Mirt stove is beneficial compared to a traditional stove?	1. Yes 2. No
130	If **Yes**, what aspect of the cookstoves is most appealing to you? *(multiple responses possible)*	1. Saves biomass fuel 2. Reduced indoor air pollution 3. Less respiratory diseases 4. Saves time for biomass fuel collection 5. Prevent deforestation 7. Others (specify) _____
131	Are you currently abandoned to use an improved cooking stove?	1. Yes 2. No
132	If **Yes**, what is the reason to dis-adopt an improved cooking stove? *(multiple responses possible)*	1. Not compatible with the local cooking practice 2. Does not heat the indoor area 3. Does not provide for indoor lighting 4. Lack of maintenance 5. Not possible to sit around the fire 6. Others (specify) _____

Part 11: Children's School Attendance and Resource Collection Activities (for school-age children ≥ 7 years)

133	Did the school-age child participate in fuelwood, water, and fodder collection activities for your household in the past seven days?	1. Yes 2. No
134	If **Yes**, how long did it take to fetch water for a round trip?	_____ minutes/hours
135	If **Yes**, on average, how many hours/minutes did you spend collecting fuelwood for a round trip?	_____minutes/hours
136	Does the household use a pack animal to collect fuelwood and water?	1. Yes 2. No

Children School Attendance

137 Child No.	138 Sex of the child 1. Male 2. Female		139 Age of child in years	140 Are you a 1st, 2nd, 3rd or other born?	141 Child r/p to HH head? 1. Own 2. Other		142 Age of child when he/she first started grade 1?	143 Does the child currently attend school? 1. Yes 2. No		144 If Yes, what grade is the child currently attending?	145 Does the child combine schooling with water, fuelwood & fodder collection activities? 1. Yes 2. No		146 Has the child ever missed school because of these activities? 1. Yes 2. No		147 If Yes, how many school days did the child miss in total? 1. 1-5 days 2. 5-10 days 3. > 10 days			148 Did these activities affect child-school attendance, homework, & study time? 1. Yes 2. No	
	1	2			1	2		1	2		1	2	1	2	1	2	3	1	2
	1	1			1	1		1	1		1	1	1	1	1	2	3	1	1
	1	2			1	2		1	2		1	2	1	2	1	2	3	1	2
	1	2			1	2		1	2		1	2	1	2	1	2	3	1	2
	1	2			1	2		1	2		1	2	1	2	1	2	3	1	2
	1	2			1	2		1	2		1	2	1	2	1	2	3	1	2

149	Is there any child in the household delayed in school enrolment?	1. Yes 2. No
150	If Yes, what is the major reason for the delay? *(multiple responses possible)*	1. Inability to pay school fees and uniform 2. Work at home in water, fuelwood and fodder collection 3. Work on the farms 4. Illness 5. The parent is not interested in the child's education 6. Others (specify) _____
151	Is there any child in the household who drop out of school?	1. Yes 2. No
152	If Yes, what is the reason for drop-out? *(multiple responses possible)*	1. The child is required for farm work 2. Being responsible for water, fuelwood, and fodder collection 3. The school is too far 4. Illness 5. Others (specify) _____
153	Does the school-child experience problems due to water, fuelwood, and fodder collection activities? *(multiple responses possible)*	1. Class Absence 2. Drop-out 3. Low performance 4. No time to study 5. Tired of school 6. Too little time to rest 7. Others (specify) _____

Key informant interview guide for elderly interview participants

1. How old are you? How many years did you live in this area?
2. What is your observation in your life regarding the following?
   a) The forest resource of the Semien Mountains National Park:
      i. Is there any change in the size of the park's natural forest for the last 30 years? Does its size increase/decrease/no change?
      ii. What do you think is the cause of such a change in size?
      iii. Does the change in forest cover have any effect on community livelihoods?
      iv. If yes, state the major problems the community faced.
   b) Agricultural land size per person:
      i. Does its size increase/decrease/no change?
      ii. What do you think is the cause of such a change in size?
   c) Grazing land size:
      i. Does its size increase/decrease/ no change?
      ii. What do you think is the cause of such a change in size?

Key informant interview guide for local people

1. How do you perceive the population of your community over the past 30 years? Yes No
2. If **YES**, what do you think has caused the population increase?
3. How do you perceive the forest resources in and around the national park over the past 30 years?
   a. Increase b. Decrease No change
4. What do you think causes land cover changes in the SMNP?
5. What kind of resources does the community obtain from the SMNP?
6. Are there any rules governing the resource use in the national park?
7. For what purpose does the community do their activities within the park
8. Are there areas where the collection is restricted/allowed in the park?
9. Do you or the community understand the function of the park?
10. What are the most important ecosystem services obtained from the national park forest resources?
11. What are the perceived pressures on the SMNP forest resources?
12. Community involvement in the conservation of the SMNP biodiversity?
13. What have you observed on forest cover around your village over the last 30 years?
14. How the forest cover changes affected the availability of ecosystem services to your households
15. How have forest cover changes affected the travel time and distance to gather forest and forest products?
16. Have you ever faced a fuelwood shortage?

Interview schedule for improved stove users

1. Do you know about improved cookstoves?
2. Describe to me any improved cook stove model you know.
3. How did you know about improved cookstoves?
4. When did you acquire your improved cookstoves?
5. Why did you decide to acquire an improved cook stove?
6. What were you using to cook before you obtained an improved cook stove?
7. What are the advantages of using this stove over the one you had?
8. What are the disadvantages of using this stove compared to the old one?
9. Was it difficult to use the new stove?
10. Do you use your cook stove for all dishes you make?
11. Have you made any modifications to your new stove?
12. What would be the reasons if you stopped using your improved cook stove?

Interview Guide for Non-Users

1. Do you know about improved cookstoves?
2. What are the features of an improved cook stove?
3. Where did you obtain the information about improved cookstoves?
4. Why aren't you using an improved cook stove?
5. If you decide to get one, what factors would you consider?
6. What do you know are the advantages of using an improved cook stove?
7. What do you know are the disadvantages of using an improved cook stove?

Key Informant Interviews Guide for Institutions

1. Does your institution have any strategies to sensitize the public on the benefits of using ICS?
2. What strategies, if any, do you use to sensitize the public on the adverse effects of traditional stoves use?
3. Does your office offer services and support to potential users and producers of ICSs? If so, what are they?
4. In your experience, what are the most likely barriers to ICSs adoption in urban areas?

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