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The Influence of Protected Area Exposure on Household Wellbeing in Uganda: A Multidimensional Poverty Approach

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ABSTRACT

This dissertation examines the impact of exposure to protected areas (PAs) on household wellbeing in Uganda, employing a multidimensional poverty (MDP) framework. Drawing on Sen's capability approach and other notable theories of poverty determinants, the study utilises logistic regression analysis of data from the Uganda National Panel Survey (2015–16) alongside other micro and spatial factors to test the association between PA exposure and household wellbeing. In accordance with other aggregated conservation-development studies, findings indicate no significant relationship between PAs and MDP once spatial and household-level characteristics are considered. Instead, factors such as proximity to urban areas, human presence, and access to economic centres emerge as primary determinants of wellbeing regardless of protection status. These findings illuminate the heterogeneous objectives of protected areas and their resultant divergent effects on local community wellbeing, suggesting an improvement of categorisation data and case-by-case explorations of their causal mechanisms as key objectives for future research.

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1 INTRODUCTION

As international development efforts continue to capture synergies with climate mitigation objectives, protected areas (PAs) have become a critical initiative in both the Sustainable Development Goals and the Paris Agreement. (Sacherer et al., 2022). Today, over 15% of the world's terrestrial surface is formally protected – an unprecedented expansion fuelled by mounting evidence that intact ecosystems deliver critical benefits to biodiversity and the environment (Geldmann et al., 2019). Yet alongside these ecological benefits, there is growing concern that PAs may impose unintended socioeconomic costs on adjacent communities, especially in low-income countries where rural households depend heavily on natural resource use for livelihoods (Brockington, Duffy & Igoe, 2008).

Uganda exemplifies this tension. Since the 1990s, the country has achieved remarkable gains in improving multidimensional wellbeing primarily through agricultural development (Nkengne, 2016). At the same, Uganda has designated 711 protected sites that cover roughly 16% of its land area (Protected Planet, 2024). While some villages report new income opportunities via ecotourism and regulated resource harvesting (Naughton-Treves, Alix-Garcia & Chapman, 2011), others cite crop losses, restricted fuelwood access, and evictions (Tumusiime, Vedeld & Gombya-Ssembajjwe, 2011). These mixed outcomes underscore the need for a wider understanding of how PA exposure influences household wellbeing at a national context.

This dissertation investigates the relationship between PA exposure and household wellbeing in Uganda through a multidimensional poverty (MDP) framework. Drawing on Sen's capability approach, I employ the World Bank's Multidimensional Poverty Measure (MPM) – which integrates monetary, educational, and basic-service deprivations – as this study's outcome variable to capture overlapping deprivations that income alone cannot reveal (Alkire & Santos, 2013). The study covers a pivotal period, 2015-16, when Uganda's poverty alleviation momentum began to slow, raising questions about whether households near PAs are inadvertently trapped in spatial poverty due to reduced access to land and forest products.

I begin with a critical review of the ongoing academic discussion around PAs and wellbeing, highlighting the key debates and challenges faced both internationally and in Uganda. In this section, I synthesise my research into a MDP conceptual framework which serves as a theoretical foundation for my analysis. Following this discussion, I outline my robust quantitative methodology which aims to answer this study's research question using multivariate logistic regression. Robustness checks include alternative specifications, accounting for outliers, and diagnostic tests for model fit. Ethical considerations and limitations of the study are discussed and reflected to preserve the integrity of this research.

The study's analysis finds that household wellbeing in Uganda is unaffected by PA exposure, suggesting that households within 15km of PAs have comparable odds to being classified as multidimensionally poor to households >15km away. The model indicates that wellbeing is determined by other geographical characteristics which influence a household's ability to escape spatial poverty traps. These findings demonstrate the strong variance in design across all PAs, highlighting the range of objectives these initiatives can have (Naidoo et al., 2019; Mammides, 2020).

2 LITERATURE REVIEW

This chapter critically reviews the current academic discussion around the role of PAs and their impact on wellbeing within an MDP framework. I begin by outlining the definition and measurement of MDP, noting its advantages and limitations as a wellbeing metric. I then examine PA objectives and their influence on MDP, focusing on Uganda's varied local outcomes and the rationale for its selection. Finally, I develop a conceptual framework to assess how PA exposure affects household MDP in Uganda.

2.1 DEFINING AND MEASURING MULTIDIMENSIONAL POVERTY

As a concept, poverty is one of the most significant challenges faced by most countries and is an issue which resonates deeply worldwide (OECD, 2023). However, from an economic perspective, defining and measuring poverty is still a heavily contested issue (Wang, Shu and Lu, 2023). Questions such as what makes a household 'poor' and how to aggregate this classification within a population are significant concerns within the conceptualisation of poverty (Konkel, 2014). Relatively poor individuals often face severe challenges in employment, education, and health, which are driven by a complex interplay of household and structural factors which may both serve as advantages and barriers to escaping poverty (White, 2020). However, despite this multitude of determinants and indicators, all approaches to defining poverty are unified by the idea of having less than an absolute or relative benchmark (Hagenaars and de Vos, 1988), and the need for poverty to be measured in the context of a group or community (Alkire, 2015). Therefore, at its most basic level, poverty refers to the idea of having less than a defined measure of wellbeing which restricts one's basic needs within the context of a wider society (Saunders, 2011).

While this framework may clarify the concept of poverty, deciding which measures and benchmarks should identify whether a household is poor are much more open-ended questions. For the most part, despite being widely understood as a multifaceted concept, poverty has traditionally been measured from a uniquely monetary perspective, typically by income, which is unrepresentative of a household's wider deprivations (Bourguignon and Chakravarty, 2019). In response to these concerns, the multidimensional approach to poverty measures a range of benchmarks beyond income to provide a more wholistic understanding of poverty, underlined by Sen's capability-functionalist approach to wellbeing (Sen, 2006; Wang, Shu and Lu, 2023). This perspective understands wellbeing as the composite measure of whether an individual has the functioning and capability to do the things they value (Sen, 1999, 2006). The multidimensional approach to poverty operates within this conceptualisation of wellbeing to create an index representative of a household's capacity to achieve these goals based on multiple overlapping deprivations (Alkire and Santos, 2013; OPHI-UNDP, 2024). These deprivations typically include fundamental components of wellbeing such as education, health, and living standards, which previous income-based measures were unable to account for (Putri, Shafiai and Ismail, 2024).

However, the introduction of multiple indicators within a single measure introduces several new limitations for MDP as a representation of wellbeing. On one hand, it is often criticised for its 'ad-hoc' selection of dimensions, which will inevitably fall short of providing a complete picture of a household's level of wellbeing (Ravallion, 2011). In addition, its arbitrary weighting of its dimensions may result in varied representations of wellbeing when applied across contexts, which a standardised weighting of MDP is unable to account for (Deyshappriya and Feeny, 2021). Finally, small changes in welfare or deprivation status can lead to sudden jumps in poverty measures, which may unfairly penalize development policies that aim to equalize welfare (Duclos et al., 2016). Overall, it is apparent that while MDP may provide a more comprehensive picture of a household's wellbeing than other traditional measures, it is still an imperfect measure which attempts to capture complex and overlapping dynamics of wellbeing within a single index. However, despite these limitations, MDP's discrete measure and use of important non-monetary indicators within its index make it a suitable indicator of wellbeing.

2.2 MULTIDIMENSIONAL POVERTY AND PROTECTED AREAS

Protected areas (PAs) are geographical spaces primarily designated for biodiversity and ecosystem protection, which include national parks, wildlife reserves, forest reserves, and other types of conservation zones (Miranda et al., 2016). In recent decades, the global network of PAs has expanded to cover roughly 15% of the world's terrestrial surface, representing one of the most important conservation strategies worldwide (Geldmann et al., 2019). As a result of their widespread growth and effectiveness of their environmental conservation strategies, PAs have been increasingly adopted as a mechanism for climate mitigation and international development. Despite this integration however, PAs are often criticised for impacting the livelihoods of local communities, particularly those in the Global South, where communities may rely on agriculture and local natural resources (Mammides, 2020). In this regard, the restrictive policies of many PAs may limit anthropogenic activities, creating spatial poverty traps which impact several dimensions of a household's wellbeing (Bird, 2019). Consequently, the linkages between PAs and poverty are a contested issue, with many arguing for a greater integration of both objectives (Andam et al., 2010). Therefore, as PAs continue to grow as a mechanism for ecosystem protection and climate mitigation, it is integral to better understand their influence on MDP goals.

2.2.1 Integrating Multidimensional Poverty Goals into Conservation Policies

The dynamic between ecosystem protection and wellbeing is heavily contested within environmental literature. PAs worldwide vary considerably in the level of restrictions placed on their designated locations, as well as the overarching objectives of their conservation efforts (Leroux et al., 2010). The degree of oversight needed to effectively manage these areas is also dependent on the individual legislative and regulatory standards of each project, therefore creating a wide range of conservation approaches which may carry significantly different impacts on the livelihoods of local communities (Mammides, 2020). Therefore, it is important to critically assess the key approaches to integrating development objectives within PA efforts.

On one hand, Adams et al., (2004) argue that conservation efforts and poverty reduction are fundamentally distinct objectives and therefore should be pursued in isolation of one another. This approach suggests that policies which attempt to address both objectives may compromise their individual effectiveness due to intrinsic trade-offs and cost-effectiveness (Ferraro and Hanauer, 2011). From this perspective, PAs are understood as a uniquely environmental mechanism intended to safeguard biodiversity and ecosystems and therefore do not need to address the needs of socioeconomic needs of local communities (Mammides, 2020). Turner et al. (2012) refute this approach by advocating for a more integrated perspective, suggesting appropriately designed PAs provide opportunities to improve the livelihoods of local communities while meeting both environmental and climate goals. This viewpoint argues that the long-term success of conservation outcomes critically depends on the involvement and cooperation of local communities, indicating that PAs cannot ignore the structural and local contexts of their designated locations (Andrade & Rhodes, 2012).

While both arguments carry compelling arguments on the purpose and objective of PAs, there is a more nuanced perspective which acknowledges the contextual differences between conservation projects. This approach suggests that while PAs should continue to have the primary aim of ecosystem conservation, these objectives must be pursued without imposing negative externalities on local populations (Roe and Elliott, 2004). This perspective comes in response to several cases where local communities have suffered disproportionately and experienced substantial costs due to their exposure to PAs access (Brockington, Duffy and Igoe, 2008). Therefore, it is imperative to understand the mechanisms behind the influence of PAs on wellbeing, and how policymakers can better integrate these concerns into conservation design.

2.2.2 Mechanisms of Protected Areas' Impact on Multidimensional Poverty

The relationship between PAs and wellbeing can be effectively understood through a spatial poverty framework, which establishes the links between a household's geographical capital and its MDP status (Bird, 2019). Spatial poverty refers to the idea that households located in rural or remote areas are more likely to experience MDP due to lower productivity and relatively weaker linkages to markets and other areas of economic opportunity. These geographical and institutional limitations may therefore lead to spatial poverty traps, impacting multiple dimensions of wellbeing (Bird, McKay and Shinyekwa, 2010). Consequently, the presence of poorly planned PA policies may further contribute to a household's low geographical capital, therefore exacerbating existing spatial poverty traps. On one hand, PAs tend to be located far from economic centres on agriculturally undesirable land due to the inherently rurality of natural landscapes and other terrain deemed suitable for environmental protection (Joppa and Pfaff, 2009). Therefore, areas experiencing spatial poverty traps are more likely to be sites of conservation efforts (Ferraro, Hanauer and Sims, 2011). However, whether PAs serve as a determinant of wellbeing within this framework or are simply correlated with other confounding spatial factors is unclear (den Braber, Evans and Oldekop, 2018). Therefore, estimating their relationship through a spatial poverty framework is integral to understand the extent at which PAs influence household MDP in their different geographical contexts.

Within this framework, the primary mechanism through which PAs may adversely influence household MDP is via restrictions placed on local access to critical natural resources used by local communities (Ferraro, Hanauer and Sims, 2011). When PAs restrict access to resources in land with already limited agricultural potential, they risk perpetuating spatial MDP traps and therefore must be adequately planned to avoid such issues (West and Brockington, 2006). On the other hand, when a PA serves to safeguard ecosystem services in way which is both non-restrictive and sustainable, conservation efforts can effectively meet both environmental and development objectives (den Braber, Evans and Oldekop, 2018). In these cases, PAs may be able to improve land with limited agricultural potential to increase wild plant and animal populations, improving agricultural capacity. In addition, PAs which provide incentives for tourism, such as national parks, can provide significant benefits and economic opportunities for local communities (Naidoo et al., 2019). Consequently, the range in impacts of PA initiatives on local wellbeing varies significantly depending on their design and structural contexts.

From a wider perspective, it is difficult to generalise the impacts of a global network of over 200,000 officially recognized PAs on an outcome as conceptually debated as MDP. On one hand, many researchers argue that the observed negative impacts of PAs may represent exceptions rather than the normative experiences of communities (Qin et al., 2019). Recent empirical evidence suggests while households near PAs tend to be poorer, this may not be attributed to PAs themselves. Quasi-experimental studies covering Bolivia (Canavire-Bacarreza and Hanauer, 2013), Cambodia (Clements et al., 2014), Nepal (den Braber, Evans and Oldekop, 2018), and Costa Rica, and Thailand (Andam et al., 2010) collectively indicate positive or neutral outcomes on wellbeing associated with PAs, indicating they may not be as harmful as some researchers suggest. Common themes from these studies include benefits from increased tourism and enhanced socioeconomic opportunities, challenging the notion that environmental conservation inherently conflicts with local community welfare. However, due to considerable methodological variability – including differences in data sources, methodologies, and poverty indicators – direct comparisons between studies are challenging, suggesting caution in generalizing their findings (Pullin et al., 2013). To date, researchers have yet to reach a consensus regarding the effects of PAs on wellbeing and poverty, highlighting considerable variability in local outcomes (Brockington and Wilkie, 2015). Such variability underscores the critical importance of adapting PA initiatives to specific local environmental and socioeconomic contexts.

2.2.3 Challenges Faced by Uganda

In terms of individual countries, Uganda provides an excellent case study to examine the relationship between PAs and wellbeing. Since the 1990s, Uganda's extreme poverty rate has declined by nearly 3% annually, making it one of Sub-Saharan Africa's most rapidly developing countries (Nkengne, 2016). This growth is reflected by rise the non-monetary wellbeing of Ugandan households, which is shown by the decrease in infant mortality, an increase in the primary education net enrolment rate, and a greater ownership of modern household assets (Nkengne, 2016). Much of the reduction in poverty during this period is attributed to significant growth in agricultural income which particularly benefits poorer households. Agriculture accounts for roughly 4/5s of Uganda's economy, which typically consists of informal, low-investment activities such as crop farming and small-scale retail trading (Ingham and Lyons, 2024). At the same time, Uganda has an extensive network of 711 recognised PAs, the majority of which are forest reserves. Roughly 16% of Uganda's terrestrial surface area is considered protected, which represents the median level of PA presence across other Sub-Saharan African countries (Protected Planet, 2024). Consequently, Uganda's position as one of the fastest developing countries in the region makes it an effective case study to assess whether higher PA exposure has impacted households' wellbeing in a period of high poverty reduction.

Several high-profile case studies observing PAs in Uganda have suggested a mixed direct impact on the livelihoods of local communities, thus reinforcing the need to better understand their relationship within its national context. On one hand, Tumusiime, Vedeld and Gombya-Ssembajjwe (2011) found that several rural communities in the

Western region of the country experienced significant costs and detriments to their livelihoods from the establishment of the Bwindi Impenetrable National Park in 1991. Following the park's declaration, many local people experienced physical eviction, tighter restrictions to accessing their natural resources, and an increased danger of wild animals raiding their crops. While the study also acknowledges several benefits the park brought to the local economy, such as increased tourism and new employment opportunities, it concluded that its costs outweighed the benefits, suggesting a detrimental effect on local wellbeing. However, in another instance, research surrounding Kibale National Park – another PA in the same region of Uganda – showed no evidence of exacerbating local poverty traps and provided a level of protection against farm loss among the most vulnerable households (Naughton-Treves, Alix-Garcia and Chapman, 2011). In this case, two major national parks in the same area have been shown to have widely contrasting impacts on local communities, representing their inconsistent implications within MDP and wellbeing. In terms of forest reserves, Uganda's preparation process for Reducing Emissions from Deforestation and Forest Degradation (REDD+)[1] has also come under criticism for limited stakeholder representation, repressing local democratic participation in favour of governmental actors and select NGOs (Mbeche, 2017). In the context of PAs, which often need local participation to be effectively managed, this lack of representation may enable weak foundations for the strength of REDD+ initiatives from inducing meaningful change in the livelihoods of local communities (Turner et al., 2012). In light of these mixed responses to PAs, a more comprehensive assessment of their impacts of local wellbeing is needed specifically in Uganda to understand the scale of these concerns.

2.3 CONCEPTUAL FRAMEWORK

When assessing the multidimensional relationship between exposure to PAs and wellbeing in a national context, it is necessary to establish a MDP conceptual framework to serve as a foundation for my analysis (Fisher et al., 2014). The framework I have

[1] REDD+ is a major international climate mitigation policy framework which uses forest reserve PAs as its mechanism for achieving emissions reduction and international development objectives (Sacherer et al., 2022)

constructed is based on the following three theories of poverty: human capital theory (Schultz, 1961), life cycle of poverty (Rowntree, 2000), and spatial poverty theory (Bird, 2019). These theories are underpinned by the neoclassical approach to poverty dynamics, which emphasises the role of uneven endowments of skills, talents, and capital which influence a household's ability to escape poverty in a market-based competitive economic system (Akamobi, Anumudu and Ugwuanyi, 2023). Human capital theory and life cycle of poverty represent household characteristics which capture micro-level determinants of wellbeing unobserved by spatial variables (Wang, Shu and Lu, 2023). By anchoring this model to established theories of poverty and wellbeing, we can interpret the influence of PA exposure on household MDP alongside other major determinants of wellbeing, grounding this relationship within the wider established MDP literature (Luft et al., 2022). In this section, I will unpack the determinants of each theory and justify their inclusion within this framework.

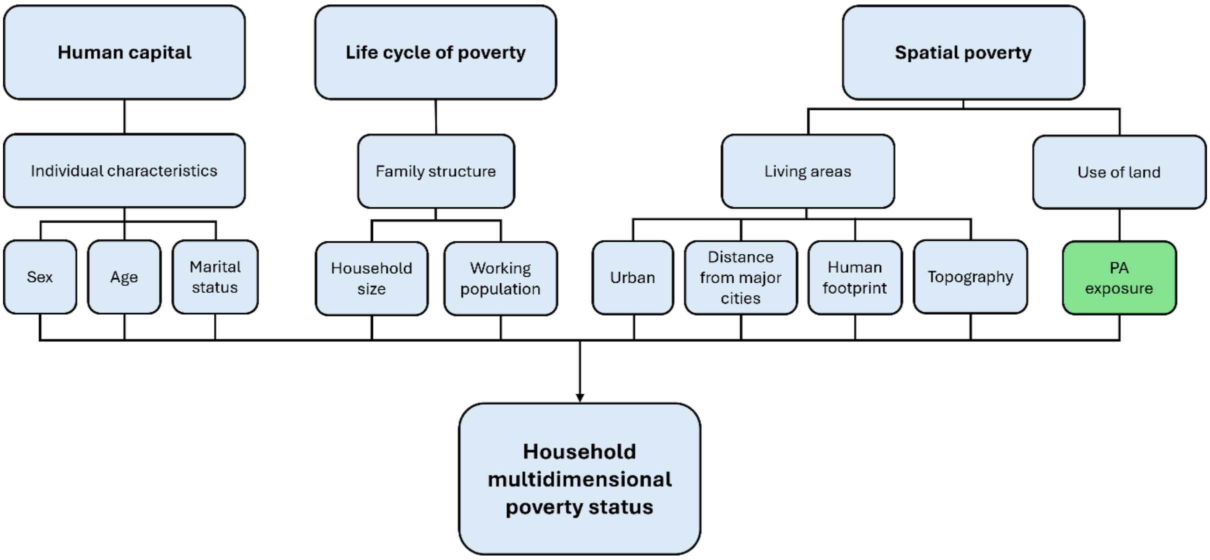
Firstly, Schultz's (1961) theory of human capital, which argues that individual characteristics such as sex, age, and marital status can affect the accumulation of human capital and therefore influence a household's wellbeing. This approach acknowledges the structural barriers to escaping poverty that may be disproportionately experienced by women, people furthest from working-age, and those not married (Wang, Shu and Lu, 2023). As a result, the impact of geographical policies will be influenced by individual household demographics and therefore should be integrated into my MDP framework.

Secondly, Rowntree's (2000) life cycle of poverty theory suggests that a household's wellbeing is closely linked with the significant life events of its family. He argues that factors such as a household's size and it working capacity will have an immediate effect on its ability to escape poverty. In this case, a household's potential to absorb multiple streams of income and how far resources are shared are significant determinants of its MDP and thus will be included in this framework.

Finally, spatial poverty theory understands a household's geographical capital as a key determinant of its wellbeing (Bird, 2019). Spatial poverty traps may be influenced both by the structural factors of a household's spatial capital, such as its access to economic centres, its geographical features, and the use of its land (Bird, McKay and Shinyekwa, 2010). In this research design, I introduce PA exposure into this theoretical framework to observe its effects within the wider context of a household's geographical capital, effectively controlling for other confounding factors.

As a result, this study's conceptual framework is visualised in Figure 1.

Figure 1: Determinants of multidimensional poverty among households in Uganda – Conceptual Framework



Using this framework, this study aims to examine the scale and strength of the influence of PA exposure on household wellbeing in Uganda via a MDP conceptualisation. Overall, given the multifaceted objectives of PAs and strong evidence of their mixed socioeconomic impacts, I argue that household wellbeing is attributed more to other important spatial factors which go beyond protection status (Naidoo et al., 2019). Therefore, the findings of this model will be grounded in existing PA and MDP literature to answer the following research question:

To what extent does exposure to PAs have an influence on household wellbeing in Uganda?

3 METHODOLOGY

This chapter provides an outline of the methodology used by this study.

3.1 RESEARCH DESIGN

To assess the influence of PA exposure on household wellbeing, this study uses a statistical approach using cross-sectional secondary data to analyse the relationship between a household's MDP status and its exposure to PAs in Uganda. This approach is comprised of two statistical methods: descriptive statistics and multivariate analysis using a logistic regression model. The econometric model used in this study is constructed around the conceptual framework established in the previous chapter and therefore includes several confounding variables representative of a household's micro and spatial determinants of MDP to control for the impacts of PAs within a non-experimental analysis (Wooldridge, 2020). The main advantage of using quantitative methods in social research with large-scale data is the ability to generalise findings to broader populations, increasing the external validity of the research (Savela, 2018).

This model examines the MDP of 2,875 randomly sampled Ugandan households to create a national estimate of the influence of PAs on MDP. By analysing the influence of PAs at the household level rather than through a broader area-based headcount ratio, the model captures important nuances in micro- and structural-level determinants of MDP that would otherwise be unobserved in aggregated area-level analyses (Ogwumike and Ozughalu, 2016).

This study adopts a post-positivism epistemology by examining statistical trends within datasets, minimising variation from these trends, and applying these findings to a larger population (Godwin et al., 2021). Applying these findings from sample to population requires justifying generalisations, informed choice of variables, and avoiding biases in the analysis (Black, 1993).

3.2 DATA

To assess the impact of PAs on household wellbeing in Uganda, the model used by this study requires data grounded in the following components of the conceptual framework:

1. Multidimensional poverty
2. Human capital theory
3. Life cycle of poverty
4. Spatial poverty theory

In this section, I will explain and justify my selection of every variable used in this study. Table 1 shows the variables and data sources used to represent each component below.

Table 1: Summary of variables and sources used in study

Variable	Source
Multidimensional poverty	
Multidimensional Poverty Measure	World Bank Living Standards Measurement Survey
Human capital theory	
Sex of head of household	World Bank Living Standards Measurement Survey
Age of head of household	
Marital status of head of household	
Life cycle of poverty	
Household size	World Bank Living Standards Measurement Survey
Working population	
Spatial poverty theory	
Urban/rural status of household	World Bank Living Standards Measurement Survey
Protected area exposure	World Database on Protected Areas
Distance from nearest major city	Esri World Cities Database
Human Footprint Index	Mu et al., 2022
Mean slope	EarthEnv Global Topography
Mean elevation	

3.2.1 Multidimensional Poverty Measure

As this study's outcome variable, I have chosen the World Bank's Multidimensional Poverty Measure (MPM) to represent household wellbeing in Uganda. MPM's inclusion of a monetary measure makes it a suitable measure of MDP within policy analysis, such as the case of PAs examined in this study, as well capturing both the economic and livelihood impacts posed by PAs (Diaz-Bonilla et al., 2023). In addition, MPM's monetary indicator can be adjusted to national contexts, making it a more meaningful measure for this study's focus on Uganda than the OPHI-UNDP's more internationally focussed Multidimensional Poverty Index (MPI) (Decerf and Fonton, 2023). While MPM is often criticised for being a simpler methodology than MPI, it is a more appropriate index in national contexts and is therefore suitable as the outcome variable of this study.

The MPM is comprises of six indicators representative of three equally weighted dimensions of wellbeing: monetary, education, and access to basic services. These indicators are defined as binary variables of either 0 or 1, where 1 means the household is deprived in that aspect. The monetary dimension uses Uganda's 2016/17 national poverty line of US$1.04 in daily consumption as its benchmark (World Bank, 2016). Households are identified as deprived if their total weighting adds up to 1/3 or greater and are therefore represented as poor (1) or non-poor (0) (Diaz-Bonilla et al., 2023). Table 2 below shows a breakdown of the indicators and weightings used in MPM.

Table 2: World Bank Multidimensional Poverty Measure (Summary in Appendix 1)

Dimension	Indicator	Deprived if:	Weight
Monetary	1. Daily consumption	Daily consumption or income is less than Uganda's national poverty line of $1.04 per person (World Bank, 2016)	1/3
Education	1. School attendance	At least one school-age child up to the age of grade 8 is not enrolled in school.	1/6
	2. Years of schooling	No adult in the household (age of grade 9 or above) has completed primary education.	1/6
Access to basic infrastructure	1. Electricity	The household has no access to electricity.	1/9
	2. Source of water	The household has no access to clean water	1/9
	3. Sanitation	The household does not have access to improved sanitation (flush toilet or similar)	1/9

Source: World Bank, 2020

The data used to construct each household's MPM, as well as all other household-level independent variables, are given by the Living Standards Measurement Survey (LSMS) published by the World Bank (UBOS, 2019). The LSMS is a global programme which monitors population, health, and agricultural indicators at the household level in developing countries. Surveys under this programme use randomly selected households from census-based sampling units (known as enumeration areas), allowing surveys to be representative at a national level (Grosh and Glewwe, 1998). Surveys also often include cluster-based geographical coordinates for each household, allowing for geospatial analysis of their local environment (Ssewanyana and Kasirye, 2020). All household data used in this study is sourced from the Uganda National Panel Survey (UNPS) 2015-16, produced by the Uganda Bureau of Statistics, which contains detailed cross-sectional microdata for 3,145 randomly selected households across Uganda, collected over a 12-month period between 2015 and 2016 (UBOS, 2019). This time frame of the data was chosen to coincide with the gradual slow-down in economic growth and poverty reduction in Uganda in the early 2010s, serving as a useful point in time to estimate whether the households which had remained the poorest were impacted by their exposure to PAs (Nkengne, 2016).

I have chosen the LSMS as the source of all household data used in this survey due to its depth of information and quality controls on all key aspects of a household's livelihood, including the variables used in this study (Scott, Steele and Temesgen, 2005). However, while the smaller sample size of the LSMS's questionnaires lower the risk of non-sampling error and ensure higher quality controls, this also presents issues on the representativeness of the available microdata (Grosh and Glewwe, 1995). While the LSMS surveys may provide detailed and high-quality household data for quasi-experimental research, they are typically representative only at the national level due to their modest sample sizes.

3.2.2 Human Capital and Life Cycle of Poverty

In this section, I will explain and justify the selection of all variables in this analysis informed by human capital and life cycle of poverty theories. Because of this study's unit of analysis, the individual characteristics of the family head will serve as a representation of the entire household. This approach assumes the head is the main source of income, and thus barriers to wellbeing faced by this individual will likely extend to the entire household (Bookwalter, Fuller and Dalenberg, 2006). All variables are given at the household level and are sourced from the UNPS 2015-16.

When adopting a human capital perspective, several individual characteristics are understood to have a structural influence on their wellbeing. One of the most significant barriers in this regard is gender, with women facing various unique discriminatory structures and processes unexperienced by men (Covarrubias, 2023). Another barrier is age, which can impact an individual's physical and labour ability, increasing vulnerability to poverty (Chen, Leu and Wang, 2019). Finally, the marital status of the household head is understood as a key determinant of wellbeing, with married heads less likely to experience MDP. This is underpinned by the assumption that married households are likely to have increased responsibilities and an integration of resources, therefore generating better economic opportunities (Mengistu, Mekonen and Aynalem, 2025). Within a human capital framework, these three characteristics are understood as the most significant determinants to a household's multidimensional wellbeing and therefore will be included as variables in this study (Chen, Leu and Wang, 2019).

In terms of the life cycle of poverty, Rowntree (2000) argues that significant life events and family structure are immediate determinants of poverty and wellbeing. For one, the size of a household will have a large influence on its opportunities and barriers to wellbeing, under the assumption that more members will strain household budgets by increasing the amount of resources needed (Abbas et al., 2020). However, depending on the productive capacity of these members, a larger household size may also improve wellbeing. The most apparent benefit to having a larger household is also the possibility to have more sources of income, and therefore this study includes the share of members aged 18-60 who are currently employed as a determinant of MDP (Ele-Ojo Ataguba, Eme Ichoku and Fonta, 2013). Within an MDP framework, these characteristics are understood as the most important determinants of wellbeing at the micro level, which are understood to influence their wellbeing regardless of protection status or spatial capital.

3.2.3 Spatial Poverty

Finally, this section provides an overview of this model's variables informed by spatial poverty theory. Modified geographical coordinates assigned to each observed household in the UNPS were used alongside other spatial data to calculate these variables. All spatial variables were calculated in QGIS Desktop 3.34.12.

Data on PAs are given by the World Database on Protected Areas (WDPA), which offers comprehensive spatial and tabular data on all internationally recognised PAs (Bingham et al., 2019). Sources for this dataset and distribution of PA designations in Uganda are shown in Appendices 2 and 3. In my analysis, I removed PAs with a 'proposed' status and those which were not yet established by 2016, the year this study's household variables were observed. In addition, PAs are classified into different categories based on their objectives and management strategies by the International Union for Conservation of Nature (IUCN) (Leroux et al., 2010). While these categories in theory may serve as useful indicators for how restrictive PAs are on the livelihoods of their local communities, there are several inconsistencies in their measurement which reduce their reliability in large-scale empirical studies (Locke and Dearden, 2005; Joppa, Loarie and Pimm, 2008). Furthermore, there is a severe lack of information on PA categories in Uganda, with 94.7% of all areas lacking an IUCN designation (full breakdown in Appendix 4) (Protected Planet, 2024). Considering these limitations, I have decided to omit IUCN categories from my analysis and treat all PAs equally. While this will likely generalise my findings, issues of data availability and inconsistency are significant limitations in wider empirical PA research, indicating the need for a more comprehensive approach to classification (Mammides, 2020). Despite this, understanding all PAs on equal ground will nonetheless provide a general understanding of the scale of their influence on household wellbeing, laying the groundwork for further research into their dynamics of change in Uganda.

To represent PA exposure in my model, I have created a categorical variable which measures whether a household is located within 5km, 10km, 15km of a PA, conforming to previous thresholds at which PAs are understood to exert socioeconomic impacts (Oldekop et al., 2016). Representing household exposure to PAs by the distance between them reflects the notion that the impacts of PAs tend to be distributed locally, hence justifying the choice to measure their exposure based on their geographical surroundings (West and Brockington, 2006). The control category for this measure is households located >15km away from PAs, where their influence is assumed to be negligible. These categories are also informed by the distribution of households in this sample, as their density appears to plateau after 15km (as shown Appendix 5). By measuring PA exposure as a categorical measure of household distance to PAs, I can effectively capture nuances in exposure which previous studies relying on binary indicators cannot.

Within a spatial poverty framework, there are several confounding factors related to the geographical allocation of PAs which must be controlled for in this model. Because PAs tend to be located in isolated and less productive areas, people living near them may face barriers to escaping spatial poverty traps regardless of protection status (Fotso, 2006). On one hand, PAs tend to be situated in areas with unsuitable topography for human use, with generally higher elevations and steeper slopes (Mammides, 2020). Therefore, data on mean slope and elevation accessed from EarthEnv Global Topography (EEGT) and mapped to household coordinates at a $1km^2$ resolution is included to control for a household's topographical restrictions (Amatulli et al., 2018). In terms of economic barriers, households located closer to major cities are likely to have an increased access to economic opportunities, and therefore less likely face spatial poverty traps (Canavire-Bacarreza and Hanauer, 2013). Therefore, I will include each household's distance to the nearest major Ugandan city given by the Esri World Cities Database (EWCD) (ESRI, 2013). However, this measure alone does not fully reflect a household's level of isolation from other basic services and infrastructure. For this, I have chosen to include the Human Footprint Index (HFI), measured at a $1km^2$ resolution, for each household coordinate. The HFI is a composite measure of human presence given by a series of key factors associated with the economic potential and output of a region (Mammides, 2020). This index includes built environments, population density, night-time lights, crop and pasture lands, road and railways, and navigable waterways in its methodology (Venter et al., 2016). This index controls for the most significant barriers to escaping spatial poverty. Finally, whether a household is located in an urban or rural area is critical for understanding exposure to spatial poverty traps, as rural populations are often more physically isolated, face greater infrastructure deficits, and are more likely to experience chronic poverty (Bird, 2019).

3.3 Data Analysis

This section will outline the statistical methods used to answer this study's research question.

3.3.1 Descriptive Statistics

Before applying statistical analysis methods, this study will begin with a section on descriptive statistics to examine the general associations between household MDP, exposure to PA, and other variables in the model. Descriptive statistics are a key methodological step in answering this study's research question by providing an initial overview of patterns and relationships in between variables. These methods are useful in contextualising sample data through descriptions, visualisations, and summaries, laying the foundation for inferential testing (Jones and Goldring, 2021). In this section, I use summary statistics, geographical distribution figures, and cross-tabulation analysis to establish the relationship between household MDP and PA exposure within the context of the conceptual framework.

3.3.2 Regression Analysis

Following a descriptive analysis of my model, I use logistic regression to formally test the association between PA exposure and household MDP in the sample of Ugandan households. Logistic regression is an appropriate method for this model as it specialises in handling binary outcomes like the outcome variable of MDP. Unlike linear regression, logistic regression accommodates a non-linear relationship between predictors and the outcome and produces Odds Ratios (OR) which are easily interpretable indicators of association (LaValley, 2008). Therefore, the economic specification used in this study is shown below:

$$\log\left(\frac{P(MPM_i = 1)}{1 - P(MPM_i = 1)}\right) = \beta_0 + \beta_a \cdot PA_i + \sum_{b=1}^{5} \gamma_b \cdot HCLP_{bi} + \sum_{c=1}^{5} \delta_c \cdot SP_{ci} + \varepsilon_i$$

Where MPM_i represents the binary outcome variable of household MDP, PA_i represents the household's PA exposure, $HCLP_{bi}$ represents the sum of all micro-level household characteristics informed by human capital and life cycle of poverty theories, SP_{ci} represents the sum of the household's geographical characteristics informed by spatial poverty theory, and ε_i represents the error term. The sigma notations ($\sum$) represent the sum of the micro and spatial variables, the number of which included in the model are given by b and c respectively. This study uses households as its unit of analysis, which is represented by i. Statistical analysis is carried out in Stata/BE 18.0.

The logistic regression model is structured stepwise to assess the changes in the association between PA exposure and household wellbeing with the inclusion of other variables. This is to gradually control for the effect of PA exposure, first by controlling for individual and household characteristics, and then expanding the model outward to include spatial variables. Modelling this relationship stepwise allows a clearer understanding of how PAs relate to household wellbeing within the context of the individual indicators included in the conceptual framework (Żogała-Siudem and Jaroszewicz, 2021). The results are presented as odds ratios (ORs), where an OR greater than 1 indicates increased odds of being multidimensionally poor, and an OR less than 1 indicates decreased odds, relative to the reference category. Standard errors (SEs) and significance levels are also reported to evaluate the statistical strength of each association (LaValley, 2008). Through this approach, the analysis will determine whether PA exposure independently predicts household MDP once household and spatial characteristics are accounted for.

The hypothesised relationship between PA exposure and household wellbeing stems from its significance within this study's conceptual framework. As other major determinants of MDP are rooted in individual, household, and spatial poverty theories, this study specifically tests whether exposure to PAs serves as an additional determinant of household MDP. Accordingly, the following hypotheses are proposed:

H_0: Exposure to PAs has no influence on household wellbeing in Uganda

H_a: Exposure to PAs has an influence on household wellbeing in Uganda

To ensure the validity of the statistical analysis used in this study, the model used must satisfy key assumptions of logistic regression, which include correct model specification, an appropriate goodness-of-fit, an absence of multicollinearity across explanatory variables, and a lack of influential outliers in the observed data (Xiao et al., 2003). Furthermore, I assess the robustness of this study's variables, both within the PA exposure categories and MDP index, to ensure methodological stability.

3.4 ETHICAL CONSIDERATIONS

Approval from the University of Bath Social Science Research Ethics Committee (Reference: 10692-12113) was obtained, confirming this study's ethical integrity. This study is considered low-risk research as it does not involve primary data collection or any sensitive interaction with individuals. All household data provided by the LSMS programme is collected with permission from interviewees and is anonymised to withold any personally identifiable information (UBOS, 2019). Therefore, ethical considerations for this study focus on its use of publicly available secondary data, fair representation and referencing of literature, and transparent reporting of its analysis and findings.

3.5 STRENGTHS AND LIMITATIONS

By grounding the statistical model within a clearly defined conceptual framework, this study aligns its empirical analysis within established conservation-development literature, thereby enhancing its theoretical rigour and relevance (Fisher et al., 2014). The inclusion of both micro-level and spatial determinants enables a more comprehensive assessment of how PA exposure intersects with multiple dimensions of poverty (Wang, Shu and Lu, 2023). Moreover, the use of MDP as the indicator of wellbeing provides a wholistic understanding of poverty, capturing overlapping deprivations that monetary indicators alone may overlook (Alkire and Santos, 2013).

Statistically, LSMS household data provides a reliable and nationally representative sample to estimate the influence of PAs on wellbeing in Uganda (Grosh and Glewwe, 1995). In addition, the quality controls put in place significantly reduce the non-sampling error of this data, strengthening its reliability (Scott, Steele and Temesgen, 2005). The use of logistic regression also provides an effective inferential methodology to statistically test the association between binary wellbeing outcomes and other determinants of MDP (LaValley, 2008).

However, there are several important limitations of logistic regression which must be considered when discussing the findings of the model. On one hand, logistic regression identifies associations between variables, not causation (Gomila, 2021). Establishing causality would require more advanced methodologies such as randomized controlled trials or other quasi-experimental designs (Wooldridge, 2020). However, the cross-sectional nature of the dataset used in this study, along with the absence of temporal variation or exogenous shocks, limits the feasibility of applying such causal inference techniques. While causal identification is beyond the scope of this study, future research can build off this study's aggregated findings by exploiting policy changes or natural experiments to better isolate the causal effects of PAs on household wellbeing.

In addition, several limitations related to the underlying data must be acknowledged. First, the sample used in this model is not representative at sub-national levels, such as Uganda's lower administrative levels (Grosh and Glewwe, 1995). This limits the ability to draw geographically nuanced conclusions about how specific deprivations may be distributed across different parts of the country. Second, the measurement of household working rate relies on assumptions that may not fully capture the informal and subsistence-based economic activities which many households in Uganda are dependent on (Nkengne, 2016). Finally, the spatial accuracy of the data is reduced due to the distortion of household coordinates in the LSMS datasets to preserve respondent privacy (Michler et al., 2022). This process, known as spatial anonymisation, involves modifying household coordinates within a given range of their average cluster-based locations within their enumeration area. While this range is relatively small for urban areas (0-2km), rural households are offset between 0-5km from their original location, which may lead to inaccuracies when performing spatial analysis (UBOS, 2019). To mitigate this issue, PA exposure in this study is measured in 5km intervals, providing a buffer that reduces the impact of coordinate noise.

4 FINDINGS

This chapter presents this study's findings of the influence of PA exposure on household wellbeing in Uganda within the established MDP conceptual framework.

4.1 DESCRIPTIVE STATISTICS

This section provides a comprehensive analysis and description of this study's data sample within the context of the established conceptual framework.

4.1.1 Sample Demographics

The dataset used for this analysis contains data on the MDP status, PA exposure, micro and spatial poverty determinants informed by the conceptual framework across 2,857 households in Uganda. Although data for 3,145 households was provided by the UNPS, observations with incomplete data were omitted from this analysis. This included households missing key indicators for the model (such as working status and geographical coordinates), and households located in areas where HFI data is unavailable.

As the sample selection of this data relies on randomisation, it is susceptible to selection bias, which arises when a data sample fails to represent its given population (Dattalo, 2009). Additionally, limiting the sample size due to data availability issues and the selection of participating countries may introduce availability bias, potentially distorting treatment effects (Ahmed, Sutton and Riley, 2012).

Tables 3 and 4 show the sample characteristics of the variables included in this model. The tables are separated by the measurement scales of the variables to help demonstrate their respective ranges and frequencies.

Table 3: Sample characteristics of categorical and binary variables

Variable		Observations	Percent	Cumulative frequency
Households located within _km of a protected area	>15km	205	7.18	7.18
	15km	312	10.92	18.10
	10km	737	25.80	43.89

	5km	1,603	56.11	100.00
Multidimensional poverty status	Non-poor	882	30.87	30.87
	Poor	1,975	69.13	100.00
Sex of head of household	Male	1,974	69.09	69.09
	Female	883	30.91	100.00
Marital status of head of household	Married	2,140	74.09	74.09
	Non-married	717	25.10	100.00
Urban status of household	Urban	732	25.62	25.62
	Rural	2,125	74.38	100.00

Data source: WDPA and UNPS

Table 4: Sample characteristics of continuous variables

Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Age of head of household (years)	2,857	43.798	14.438	18	104
Household size (individuals)	2,857	5.195	2.686	1	25
Share of household members aged 18-60 currently employed (%)	2,857	0.215	0.332	0	1
Distance from nearest major city (km)	2,857	53.776	37.099	0.811	153.664
Mean Human Footprint Index (0-50) at 1km^2 resolution	2,857	22.977	7.674	1.630	49.083
Mean elevation (m) at 1km^2 resolution	2,857	1230.695	225.839	619.312	2207.500
Mean slope (∘) at 1km^2 resolution	2,857	2.923	2.710	0	14.844

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Table 3 shows that 69.1% of households in the observed sample are considered multidimensionally poor, noticeably higher than the World Bank's estimation of 57.8% in 2016/17 (World Bank, 2024). However, the World Bank's figure is derived from the Uganda National Household Survey, which differs in sample size and selection approach, which might have contributed to this difference (UBOS, 2021). In addition, only 7.2% of households are shown to be located >15km away from the nearest PA, the control group for this study. This represents a highly skewed distribution of households near to PAs and therefore will be accounted for by testing alternative exposure specifications in the model. Table 4 shows the sample characteristics for all continuous variables, which are all normally distributed.

To demonstrate the difference between the influence of PA exposure on household wellbeing, Table 5 shows the distribution of multidimensionally poor and non-poor households by their proximity to the nearest PA and cross-tabulates their relationship.

Table 5: Spatial poverty variables by MPM status

Household within _km of protected area	Non-poor observations (share of total non-poor)	Poor observations (share of total Poor)
5km	520 (59.0%)	1,083 (54.8%)
10km	240 (27.2%)	497 (25.2%)
15km	75 (8.5%)	237 (12.0%)
>15km	47 (5.3%)	158 (8.0%)
Total	882 (100%)	1,975 (100%)
Pearson chi^2 (3) = 15.72; p = 0.001; Cramér's V = 0.0742		

Data source: WDPA and UNPS

Table 5 shows a mixed influence of PA exposure on household MDP. At face value, the table shows a greater proportion of non-poor households tend to be distributed nearer to PAs than poor households and vice-versa, implying they may be associated with higher wellbeing. The large chi-square value of 15.72 and the low p-value of 0.001 also indicate a statistically signficiant relationship between the two variables. However, the Cramér's V value of 0.072 refutes this by implying a very weak association. These results indicate that while poor and non-poor households may differ in their distribution across PA exposure categories, the effect size only explains a small part of their variation in wellbeing. In response, I examine the effect of micro and spatial characteristics carry greater explanatory power.

4.1.2 Human Capital and Life Cycle of Poverty

This section details the characteristics of household MDP and PA exposure data within a human capital and life cycle of poverty framework. To illustrate this difference, Table 6 shows the differences in characteristics between multidimensionally non-poor and poor households.

Table 6: Human capital and life cycle of poverty variables by MPM status

Variable	**Non-poor**	**Poor**	**P-value**
Two-sample test of proportions			
Male-headed households (%)	68.7%	69.3%	0.765
Married head of household (%)	70.4%	76.9%	0.000
Two-sample t-test with equal variables			
Mean age of household head (years)	43.5	43.9	0.505
Mean household size (individuals)	4.2	5.7	0.000
Average employment rate (%)	29.9%	17.8%	0.000

Data source: UNPS

To test the significance of the relationship between the chosen variables and household MDP, I used a test of proportions and a two-sample t-test (depending on the variable's measurement scale) to create a p-value for each variable, which indicates the statistical significance of their relationship.

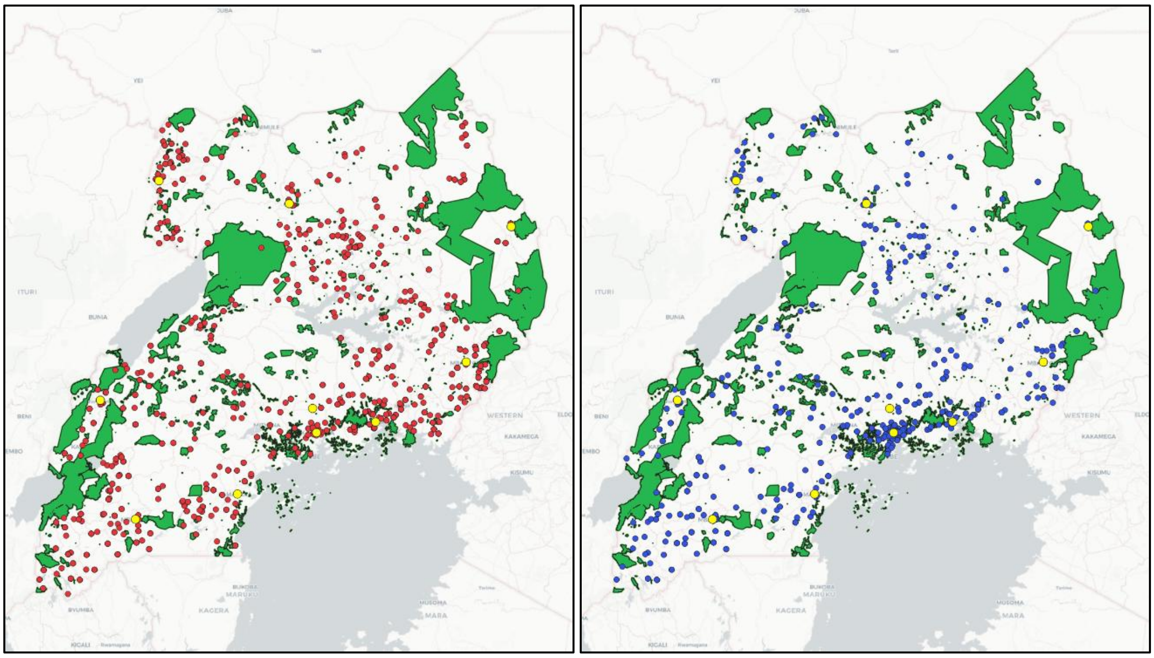
On one hand, the sex and age of the head individual are comparable between poor and non-poor households, implying these characteristics are not major determinants of MDP in the sample. This is further shown by their high p-values, implying their relationship is statistically insignificant. This refutes findings from Covarrubias (2023) and Chen, Leu and Wang (2019), who argue each characteristic is a key determinant of a household's wellbeing. On the other hand, the marital status, household size, and the employment rate of a household are all shown to significantly associated with a household's wellbeing in this study's sample, demonstrated by their low p-values, reflecting arguments by Mengistu, Mekonen and Aynalem (2025) and Rowntree (2000). In the context of PA exposure, the results of these tests imply that there are several key household-level characteristics which may influence wellbeing regardless of protection status.

4.1.3 Spatial Poverty

This section details the characteristics of household MDP and PA exposure data within a spatial poverty framework. To assess these differences, it is important to observe the geographical biases in the location of PAs (Joppa and Pfaff, 2009).

Figure 2 below illustrates these differences by showing the geographical distribution of households, PAs, and major cities in Uganda. The figure on the left charts multidimensionally poor households (represented by red points) and the right charts multidimensionally non-poor households (represented by blue points). Major cities are represented by large yellow points and PAs are represented by green-shaded areas.

Figure 2: Geographical distribution of households by MPM status



Multidimensionally poor households **Multidimensionally non-poor households**

Data source: UNPS, WDPA, EWCD

Notes: Red points = multidimensionally poor; Blue points = multidimensionally non-poor; Yellow points = Major cities in Uganda; Green areas = Protected areas.

From a geographical perspective, this figure indicates that non-poor households in this study's sample tend to be distributed closer to major cities, while poor households are more spread out across the country. Under the assumption that major cities serve as areas of high economic opportunity, this correlation implies that other spatial constraints beyond PA exposure may have a greater influence on household wellbeing (Bird, 2019).

To explore this relationship within the context of spatial poverty, Table 7 shows the differences in spatial variables between poor and non-poor households, using the same testing approach as Table 6.

Table 7: Spatial poverty variables by MPM status

Variable	**Non-poor**	**Poor**	**P-value**
Two-sample test of proportions			
Share of households located in urban area (%)	53.1%	13.4%	0.000
Two-sample t-test with equal variables			
Mean distance to nearest major city (km)	38.8km	60.4km	0.000
Mean Human Footprint Index at 1km^2 resolution (0-50)	27.8	20.8	0.000
Mean elevation (m) at 1km^2 resolution	1236.3m	1228.2m	0.379
Mean slope ($\circ$) at 1km^2 resolution	3.0$\circ$	2.9$\circ$	0.274

Data source: UNPS, EWCD, Mu et al. (2022), EEGT

On one hand, non-poor households on average are located closer to major cities, general human activity (represented by higher value of HFI), and in urban environments than poor households, shown as statistically significant by their low p-values. These variables represent strong assets in a households' spatial capital, serving as opportunities to escape spatial poverty traps (Bird, 2019). On the other hand, the mean elevation and slope are comparable in value between poor and non-poor households, implying topographical features of local envrionment are not key determinants of wellbeing in this sample. These findings are inconsistent with suggestions made by Canavire-Bacarreza and Hanauer (2013), who argue these factors have significant influence on agricultural and general development.

When comparing these figures to those in Table 5, it becomes apparent that while non-poor households may be more exposed to PAs, their wellbeing is likely to be attributed more to other geographical factors beyond protection status. The following section inferentially tests this observation within this study's conceptual framework to observe whether PA exposure is significantly associated with household wellbeing.

4.2 REGRESSION ANALYSIS

This section details the regression analysis conducted to answer this study's research question.

4.2.1 Principal Results

Table 9 presents the findings regarding the relationship between a household's exposure to PA and their MDP status in Uganda, as identified by this study's econometric model.

Table 7: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results (Summary in Appendix 6)

Variable	**(1)**	**(2)**	**(3)**
Protected Area Status			
Household located within >15km of PA	1 (.)	1 (.)	1 (.)
Household located within 15km of PA	0.940 (0.200)	0.837 (0.185)	0.969 (0.700)
Household located within 10km of PA	0.616*** (0.113)	0.617** (0.118)	1.043 (0.214)
Household located within 5km of PA	0.620*** (0.108)	0.616*** (0. 112)	0.987 (0.189)
Human Capital and Life Cycle of Poverty			
Sex of head of household		1.126 (0.216)	1.153 (0.144)
Age of head of household		0.990*** (0.00297)	0.988*** (0.00331)
Marital status of head of household		1.078 (0.130)	1.294 (0.178)
Household size		1.274*** (0.0259)	1.279*** (0.0286)
Share of household members aged 18-60 currently employed		0.477*** (0.0596)	0.766** (0.109)
Spatial Poverty			
Urban/rural classification of household			3.611*** (0.425)

Household distance from nearest major city / km			1.007*** (0.00155)
Human Footprint Index 2016			0.928*** (0.00825)
Mean elevation of household by 1km² resolution / m			1.000 (0.000281)
Mean slope of household by 1km² resolution / ◦			0.981 (0.0226)
Observations	2857	2857	2857
Pseudo R^2	0.005	0.075	0.234
Log likelihood	-1757.64	-1633.16	-1353.23

Notes: Odds Ratio; Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Column (1) shows a statistically significant positive association between household MDP and exposure to PAs. The output shows that households located between 0-10km of a PA are roughly 38% more likely to be multidimensionally non-poor than households living >15km away, as indicated by their ORs of roughly 0.62. The low p-value further indicates this association is statistically significant.

4.2.2 Human Capital and Life Cycle of Poverty

Column (2) introduces this study's micro-level variables into the model, informed by human capital and life cycle of poverty theories. After controlling for these characteristics, the protective association of living within with 0-10km of a PA remains essentially unchanged, given by their comparable OR, SE and p-values. In addition, older household heads, larger household size, and higher employment rates also show significant associations with MDP. This implies that the influence of PA exposure on household wellbeing is relatively unaffected by differences in their micro-level characteristics.

4.2.3 Spatial Poverty

However, once household geographical context informed by spatial poverty theory is accounted for in column (3), the association between PA exposure and household MDP disappears. This is demonstrated as the ORs for all PA categories narrow closer to 1 and all p-values increase to >0.05, implying a statistically insignificant neutral relationship between household wellbeing and PA exposure. In contrast, urban residence, distance from cities, and the HFI show statistically significant associations with household wellbeing, given by their low p-values. This is further demonstrated by the sharp rise in pseudo R^2 from 0.005 in column (1) to 0.234 in column (3), implying the addition of micro- and spatial values explain roughly 23% of the variation in household MDP in the study's sample compared to 0.5% for PA exposure alone.

These findings are relatively compatible with Bird's (2019) framing of spatial poverty. From a wider perspective, these findings are consistent with empirical research from several key studies who argue that PAs do not inhibit wellbeing, and are rather influenced by other spatial factors (Andam et al., 2010; Canavire-Bacarreza and Hanauer, 2013; den Braber, Evans and Oldekop, 2018; Naidoo et al., 2019).

4.3 ROBUSTNESS CHECKS

In this section, I conduct a series of tests and alternative specifications to assess the robustness of the model.

4.3.1 Alternative Specifications

To account for the skewed control group for PA exposure (only 7.2% of households located >15km away from PA), the model was re-estimated using two alternative specifications to account for this uneven distribution of households. Control groups for protection status were expanded to households located >10km (18.1% of sample) and >5km (43.9% of sample) away from their nearest PA to increase the size of the variable's reference group, improving the accuracy of the model at the expense of reduced granularity in measurement. Stepwise models using both specifications revealed no significant change in the influence of PAs on household MDP, as the OR, SE, and p-values across all categories remained relatively stable, implying the small control group has not significantly influenced the findings. Summary of alternative specifications are shown in Appendices 7 and 8.

4.3.2 Outliers

To evaluate the robustness of the logistic regression results, the model was re-estimated after omitting identified outliers. Accounting for outliers is crucial because extreme observations can distort model estimates, ORs, SEs, and overall model fit (Lukman et al., 2025). Table 10 presents the findings regarding the relationship between a household's exposure to PAs and their MDP status in Uganda, omitting outliers identified in all continuous variables in the model.

Table 8: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results without Outliers (Summary in Appendix 9)

Variable	**(1)**	**(2)**	**(3)**
Protected Area Status			
Household located within >15km of PA	1 (.)	1 (.)	1 (.)
Household located within 15km of PA	0.924 (0.216)	0.812 (0.197)	0.646* (0.170)
Household located within 10km of PA	1.265 (0.267)	1.254 (0.276)	1.010 (0.241)
Household located within 5km of PA	0.793 (0.153)	0.802 (0. 161)	0.935 (0.205)
Human Capital and Life Cycle of Poverty			
Sex of head of household		1.090 (0.144)	1.104 (0.157)
Age of head of household		0.990*** (0.00366)	0.987*** (0.00391)
Marital status of head of household		1.107 (0.162)	1.235 (0.195)
Household size		1.308*** (0.0328)	1.303*** (0.0345)
Share of household members aged 18-60 currently employed		0.573*** (0.0876)	0.725* (0.120)
Spatial Poverty			
Urban/rural classification of household			3.805*** (0.504)
Household distance from nearest major city / km			1.007*** (0.00175)
Human Footprint Index 2016			0.934*** (0.0124)
Mean elevation of household by 1km² resolution / m			1.000 (0.000449)
Mean slope of household by 1km² resolution / ◦			0.963 (0.0438)
Observations	2857	2857	2857
Pseudo R^2	0.006	0.077	0.167
Log likelihood	-1215.83	-1128.61	-1018.91

Notes: Odds Ratio; Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

When outliers are excluded, several notable changes emerge. Firstly, the association between PA exposure and household MDP is no longer statistically significant in columns (1) and (2). At the same time, households located within 15km of a PA show a marginally significant association with household wellbeing, as shown by the OR of 0.646 and p-value of <0.1, which was not observed when outliers were included. This indicates that households located further than 10-15km away from the nearest PA have greater odds of being non-poor than households located 0-10km and >15km away. Additionally, SEs generally decrease slightly without outliers, indicating more precise estimates. On the other hand, the associations between the micro and spatial variables in the model are relatively unchanged, demonstrating they were uninfluenced by extreme values.

Overall, the model's overall explanatory power, as captured by the pseudo-R^2, also declines from 0.234 to 0.167 when outliers are omitted, suggesting that extreme values had contributed substantially to model fit. These changes highlight the sensitivity of the model's initial findings to extreme observations and indicate a slightly negative association between PA exposure and household wellbeing. When omitting outliers, the findings of this model are reflective of more critical perspectives of PAs and poverty, which argue they are detrimental to household wellbeing (Ferraro, Hanauer and Sims, 2011; West and Brockington, 2006).

4.3.3 Diagnostic Exercises

For this study's analysis to be valid, the model used must satisfy the assumptions of logistic regression, which will be estimated using a series of diagnostic exercises.

4.3.3.1 Specification test

A logistic regression model is correctly specified if it is assumed to include all relevant variables, exclude any irrelevant variables, and its logistic function is a linear combination of the predictor variables. To test the model's specification, I assessed whether the squared linear predicted value adds significant explanatory power beyond the linear prediction (Xiao et al., 2003). The results indicate the squared linear predicted value is significant at the 5% level both with and without outliers, suggesting possible model misspecification. This implies that although the model explains a significant portion of the variation in household MDP, there may still be omitted variables, nonlinearities, or interactions not fully captured by the current model specifications. Outputs for specification tests are shown in Appendix 10.

4.3.3.2 Goodness-of-fit

To assess the goodness-of-fit of the logistic regression models, the Hosmer–Lemeshow test was conducted. This test evaluates whether the model is well calibrated so that its probability predictions reflect the occurrence of events in the data (LaValley, 2008). In this model, results indicate low evidence of a lack of fit both with and without outliers, supporting the adequacy of the logistic regression model for explaining household MDP in the sample. Outputs for goodness-of-fit tests are shown in Appendix 11.

4.3.3.3 Multicollinearity

Finally, the validity of the logistic regression model rests upon the assumption that no predictor variables are highly linearly correlated with each other. This is known as multicollinearity and is shown by Variance Inflation Factors (VIFs) (Xiao et al., 2003). After testing, all individual VIF values are well below the commonly used thresholds of 5 or 10 both with and without outliers, suggesting that multicollinearity is not a significant issue in either version of the model. Outputs for multicollinearity test are shown in Appendix 12.

4.3.4 Multidimensional Poverty Measure

As a multidimensional indicator, the MPM involves several methodological decisions which affect both the identification and aggregation of its values (Alkire and Santos, 2014). This section assesses the robustness of the poverty cutoffs and weights within this study's household sample.

4.3.4.1 Robustness to changes in poverty cutoff

The selection of 0.333 as the poverty cut-off in the MPM is intended to capture whether a household is deprived in at least one of the three dimensions included within the model. However, this approach to measuring wellbeing raises the question of whether households deprived in only one dimension may be truly classified as 'multidimensionally' poor (Ravallion, 2011). To test the robustness of this approach within this study's household sample, I introduce two additional poverty cut-offs of $k = 0.2$ and $k = 0.4$ as a test of restricted form of dominance. The lowest weighting for an individual indicator in the MPM model is 0.167, meaning that 0.2 may be understood as the lowest threshold for a household to be considered multidimensionally poor. On the other hand, cut-offs above 40% are considered to be overly demanding (Alkire and Santos, 2014).

To test the robustness of across the three possible poverty benchmarks, I cross-tabulate the baseline cut-off of 0.333 against the alternatives and calculate Cohen's κ statistic to observe the agreement between them. The results show that the 0.333 poverty cut-off captures roughly 90% of the same classification for both $k = 0.2$ and $k = 0.4$, implying that poor households will generally be classified as such regardless of the cut-off. Outputs for these tests are shown in Appendix 13.

4.3.4.2 Robustness to changes in weights selection

MDP indices are often criticised for their assumption of equal weightings across all dimensions (Deyshappriya and Feeny, 2021). Therefore, I test whether this study's MPM is robust to a wider range of weightings, represented by giving a 0.5 weight to one dimension and 0.25 weights to the other two in each distinct structure (Alkire and Santos, 2014). I use Spearman's and Kendall's rank correlation tests to examine how comparable the MDP statuses of this study's household sample are when different weightings are applied. Results show MPM to be very robust when doubling the monetary and education weight, and moderately robust when doubling the living standards weight. These results imply that changes to the weightings in this study's MPM do not significantly change the number of households considered multidimensionally poor, therefore implying a robust measurement of household MDP. Outputs for these tests are shown in Appendix 14.

4.3.5 Strengths And Limitations of Model

Overall, while this model satisfies most assumptions of logistic regression, demonstrates a robust MDP methodology, and finds no significant changes in findings with alternative PA categorisations, its explanatory power in is limited by its misspecification. This implies that the model is missing several variables which may not capture a significant amount of the variation in MDP in the sample, reducing reliability of results. These issues likely reflect the limited scope of the conceptual framework, which omits other important determinants of wellbeing such as social and financial capital (Chen, Leu and Wang, 2019;

Wang, Shu and Lu, 2023). To address this, future iterations of the model should incorporate a broader set of explanatory variables to capture a wider set of determinants. Nonetheless, even with potential specification gaps, the variables included in the model are firmly grounded in established MDP theory, ensuring that the model remains conceptually sound despite its statistical limitations (Fisher et al., 2014).

4.4 Contextual Discussion

Considering these findings, this study finds little evidence that exposure to PAs has an influence on household wellbeing based on the observed cross-sectional data from Uganda. These findings are consistent with wider conservation-poverty quantitative studies at both national and international levels, which have regularly found that PAs do not exacerbate poverty and often have a positive to neutral relationship with wellbeing (Andam et al., 2010; Canavire-Bacarreza and Hanauer, 2013; Clements et al., 2014; den Braber, Evans and Oldekop, 2018; Mammides, 2020; Naidoo et al., 2019). The limited explanatory power of PA exposure is underscored by the low pseudo-R^2 score of 0.005 when it's the sole predictor in the model. In addition, its large p-values and negligible ORs across all distance categories imply no reliable evidence that households living near to PAs are significantly associated with wellbeing. Even when outliers are omitted, the relative lack of statistical significance across all PA categories imply no strong change in findings.

Observing the socioeconomic influence of PAs in the context of this study's conceptual framework poses several key insights into their relationship with household MDP. This study's findings suggest that that any bivariate link between PAs and MDP within this sample of Ugandan households is primarily attributable to spatial factors rather than direct exposure to PAs themselves. PAs themselves do not significantly contribute to spatial poverty traps, while other geographical characteristics such as urban/rural classification, distance from major cities, and human presence have a more substantial and direct impact on household wellbeing (Bird, 2019). Furthermore, while micro-level household characteristics are indeed significantly associated with wellbeing outcomes, they do not appear to interact with PA exposure within this study's framework.

Consequently, the observed association between proximity to PAs and household MDP likely reflects broader spatial dynamics that influence wellbeing irrespective of a location's protection status (den Braber, Evans and Oldekop, 2018).

From a general perspective, the lack of consistency between PA exposure and household wellbeing explored in this study is reflected by the conceptual debate around conservation-development goals. As Leroux et al. (2010) highlight, PAs vary significantly in objectives, restrictions, and management approaches, resulting in varied and inconsistent impacts on the wellbeing of their local communities. The neutral association observed in this study likely stems from a general ambiguity on how development outcomes should be integrated into conservation efforts, a debate that remains unresolved in existing literature (Mammides, 2020). Grouping PAs with fundamentally different designations and objectives into one unified initiative inherently obscures specific associations between types of PAs and household wellbeing in different contexts, which is reflected by the model's neutral OR estimates for PA exposure. Therefore, while this study's analysis offers insight into the aggregated impacts of PAs on household wellbeing in Uganda, its applications within their mechanisms and contextual differences is limited by its treatment of PAs as a homogenous concept. However, it should be noted that this generalised understanding is largely a result of data constraints and inconsistent categorisation of PAs which limit the extent they can be distinguished by category and designation (Locke and Dearden, 2005; Protected Planet, 2024). Improved standardisation and applications of IUCN categories internationally would ameliorate these limitations within quantitative studies such as this one.

Overall, this study's findings contribute to a growing collection of literature which aims to contextualise the aggregated influence of PAs within different national and international contexts. However, given the current state of PA data availability and its conceptual tensions with development objectives, future research exploring the causal mechanisms and contextual differences underlying PA impacts in the specific case of Uganda would benefit from qualitative, case-by-case approaches which are able to more meaningfully explore the contextual drivers and stakeholders behind individual PAs. Overall, despite these limitations, this study provides a general overview of the impact of

PAs on household wellbeing in Uganda within an MDP framework, laying the empirical foundations for future explorations of their dynamics in Uganda.

5 CONCLUSION

This dissertation investigates the influence of exposure to PAs on wellbeing in Uganda within a MDP framework using cross-section household data. Adopting a logistic regression approach, this study analyses a nationally representative sample of 2,857 random households alongside other major determinants of MDP to answer this research question. This study contributes to existing conservation-development literature by estimating the aggregate influence of PAs on wellbeing in the previously unexplored national context of Uganda.

Within a spatial poverty theoretical framework, conservation-development literature suggests two competing hypotheses: that PAs either exacerbate household deprivations by restricting access to natural resources (Brockington, Duffy & Igoe, 2008) or generate local benefits via ecosystem services and ecotourism (Naidoo et al., 2019). Previous quasi-experimental studies in other contexts have found both neutral and positive wellbeing outcomes associated with PA exposure (Andam et al., 2010; den Braber, Evans & Oldekop, 2018). Building on these aggregated studies, the regression results reveal no direct association between PA exposure and MDP once spatial covariates are introduced, indicating that household wellbeing in Uganda depends less on PA exposure alone and more on geographical access to markets, services, and infrastructure. The neutral results also demonstrate how grouping PAs into one unified initiative obscures their unique objectives and restrictions, each of which may interact very differently with local wellbeing.

Building on these results, future studies should exploit policy changes or natural experiments to establish causality and examine heterogeneity by PA type. Investigations into the specific mechanisms – such as resource access restrictions and tourism revenues – will further clarify how conservation interventions intersect with MDP dynamics (Naidoo et al., 2019). In addition, a more robust categorisation methodology is needed for PAs to better capture the differences in objectives and restrictions across initiatives, which would improve the reliability of aggregated studies such as this one (Leroux et al., 2010).

In conclusion, this study finds that once spatial and household factors are accounted for, exposure to PAs in Uganda does not independently predict household wellbeing. These findings represent a greater understanding that PAs worldwide vary significantly in their objectives, leading to inherently divergent impacts on local wellbeing.

6 BIBLIOGRAPHY

Abbas, K., Li, S., Xu, D., Baz, K. and Rakhmetova, A., 2020. Do socioeconomic factors determine household multidimensional energy poverty? Empirical evidence from South Asia. Energy policy [Online], 146, pp.111754-. Available from: https://doi.org/10.1016/j.enpol.2020.111754.

Adams, W.M., Aveling, R., Brockington, D., Dickson, B., Elliott, J., Hutton, J., Roe, D., Vira, B. and Wolmer, W., 2004. Biodiversity Conservation and the Eradication of Poverty. *Science (American Association for the Advancement of Science)* [Online], 306(5699), pp.1146–1149. Available from: https://doi.org/10.1126/science.1097920.

Ahmed, I., Sutton, A.J. and Riley, R.D., 2012. Assessment of publication bias, selection bias, and unavailable data in meta-analyses using individual participant data: a database survey. BMJ [Online], 344(7838), pp.16–16. Available from: https://doi.org/10.1136/bmj.d7762.

Akamobi, O.G., Anumudu, C.N. and Ugwuanyi, C.U., 2023. Socio-economic determinants of multidimensional child poverty in Nigeria [Online]. Journal of Policy and Development Studies, 13(4). Available from: https://www.ajol.info/index.php/jpds/article/view/254633.

Alkire, S., 2007. The Missing Dimensions of Poverty Data: Introduction to the Special Issue. Oxford development studies [Online], 35(4), pp.347–359. Available from: https://doi.org/10.1080/13600810701701863.

Alkire, S. and Foster, J., 2011. Counting and multidimensional poverty measurement. Journal of public economics [Online], 95(7), pp.476–487. Available from: https://doi.org/10.1016/j.jpubeco.2010.11.006.

Alkire, S. and Santos, M.E., 2013. A Multidimensional Approach: Poverty Measurement & Beyond. Social indicators research [Online], 112(2), pp.239–257. Available from: https://doi.org/10.1007/s11205-013-0257-3.

Alkire, S. and Santos, M.E., 2014. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. World development [Online], 59, pp.251–274. Available from: https://doi.org/10.1016/j.worlddev.2014.01.026.

Alkire, S., 2015. Multidimensional poverty measurement and analysis. First edition. Oxford: Oxford University Press.

Amatulli, G., Domisch, S., Tuanmu, M.-N., Parmentier, B., Ranipeta, A., Malczyk, J. and Jetz, W., 2018. A suite of global, cross-scale topographic variables for environmental and biodiversity modeling. Scientific data [Online], 5(1), pp.180040–180040. Available from: https://doi.org/10.1038/sdata.2018.40.

Andam, K.S., Ferraro, P.J., Sims, K.R.E., Healy, A., Holland, M.B. and Dasgupta, P.S., 2010. Protected areas reduced poverty in Costa Rica and Thailand. *Proceedings of the National Academy of Sciences - PNAS* [Online], 107(22), pp.9996–10001. Available from: https://doi.org/10.1073/pnas.0914177107.

Andrade, G.S.M. and Rhodes, J.R., 2012. Protected Areas and Local Communities: an Inevitable Partnership toward Successful Conservation Strategies? *Ecology and society* [Online], 17(4), pp.14–14. Available from: https://doi.org/10.5751/es-05216-170414.

Bingham, H.C., Deguignet, M., Lewis, E., Stewart, J., Juffe-Bignoli, D., MacSharry, B., Milam, A. and Kingston, N., 2019. User Manual for the World Database on Protected Areas and world database on other effective area based conservation measures: 1.6 [Online]. UNEP-WCMC. Available from: http://wcmc.io/WDPA_Manual.

Bird, K., McKay, A., Shinyekwa, I., 2010. Isolation and poverty: the relationship between spatially differentiated access to goods and services and poverty [Online]. Overseas Development Institute.

Available from: https://odi.org/en/publications/isolation-and-poverty-the-relationship-between-spatially-differentiated-access-to-goods-and-services-and-poverty/ [Accessed 12 April 2025].

Bird, K., 2019. Addressing Spatial Poverty Traps [Online]. Overseas Development Institute. Available from: https://www.un.org/development/desa/dspd/wp-content/uploads/sites/22/2019/02/Spatial-poverty-traps-by-Kate-Bird.pdf.

Black, T.R., 1993. Evaluating social science research : an introduction. London: Sage.

Bookwalter, J.T., Fuller, B.S. and Dalenberg, D.R., 2006. Do Household Heads Speak for the Household? A Research Note. Social indicators research [Online], 79(3), pp.405–419. Available from: https://doi.org/10.1007/s11205-005-4925-9.

Bourguignon, F., Chakravarty, S.R. and Chakravarty, S.R., 2019. Multidimensional Poverty Orderings: Theory and Applications. Poverty, Social Exclusion and Stochastic Dominance [Online]. Singapore: Springer Singapore Pte. Limited, pp.143–166. Available from: https://doi.org/10.1007/978-981-13-3432-0_10.

Brockington, D., Duffy, R. and Igoe, J., 2008. Nature unbound : conservation, capitalism and the future of protected areas. London ; New York: Earthscan.

Brockington, D. and Wilkie, D., 2015. Protected areas and poverty. *Philosophical transactions - Royal Society. Biological sciences* [Online], 370(1681), pp.20140271–20140271. Available from: https://doi.org/10.1098/rstb.2014.0271.

Canavire-Bacarreza, G. and Hanauer, M.M., 2013. Estimating the Impacts of Bolivia's Protected Areas on Poverty. *World development* [Online], 41, pp.265–285. Available from: https://doi.org/10.1016/j.worlddev.2012.06.011.

Chen, K.-M., Leu, C.-H. and Wang, T.-M., 2019. Measurement and Determinants of Multidimensional Poverty: Evidence from Taiwan. Social indicators research [Online], 145(2), pp.459–478. Available from: https://doi.org/10.1007/s11205-019-02118-8.

Clements, T., Suon, S., Wilkie, D.S. and Milner-Gulland, E.J., 2014. Impacts of Protected Areas on Local Livelihoods in Cambodia. World development [Online], 64, pp.S125–S134. Available from: https://doi.org/10.1016/j.worlddev.2014.03.008.

Covarrubias, A., 2023. Gender and multidimensional poverty at the individual level in Mexico. Development studies research [Online], 10(1). Available from: https://doi.org/10.1080/21665095.2023.2218577.

Dattalo, P., 2009. Basic Concepts and Assumptions. Strategies to Approximate Random Sampling and Assignment [Online]. New York: Oxford University Press. Available from: https://doi.org/10.1093/acprof:oso/9780195378351.003.0001.

Decerf, B. and Fonton, K., 2023. Reconceptualizing Global Multidimensional Poverty Measurement, with Illustration on Nigerian Data [Online]. World Bank. Washington, D.C.: World Bank Group. Available from: https://documents1.worldbank.org/curated/en/099345010022340305/pdf/IDU1894308b516a1714cd6191f11302ac764ccdb.pdf.

den Braber, B., Evans, K.L. and Oldekop, J.A., 2018. Impact of protected areas on poverty, extreme poverty, and inequality in Nepal. *Conservation letters* [Online], 11(6). Available from: https://doi.org/10.1111/conl.12576.

Deyshappriya, N.P.R. and Feeny, S., 2021. Weighting the Dimensions of the Multidimensional Poverty Index: Findings from Sri Lanka. Social indicators research [Online], 156(1), pp.1–19. Available from: https://doi.org/10.1007/s11205-021-02656-0.

Diaz-Bonilla, C., Sabatino Gonzalez, C.G., Wu, H. and Nguyen, M.C., 2023. Update to the Multidimensional Poverty Measure : What's New [Online]. World Bank. Washington, D.C.: World Bank Group. Available from: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099726505242329557/idu0403d508104f7a0420b084460b7206fab6e38.

Duclos, J.-Y., Tiberti, L., Adler, M.D. and Fleurbaey, M., 2016. Multidimensional Poverty Indices: A Critical Assessment. The Oxford Handbook of Well-Being and Public Policy [Online]. Oxford University Press. Available from: https://doi.org/10.1093/oxfordhb/9780199325818.013.19.

Ele-Ojo Ataguba, J., Eme Ichoku, H. and Fonta, W.M., 2013. Multidimensional poverty assessment: applying the capability approach. International journal of social economics [Online], 40(4), pp.331–354. Available from: https://doi.org/10.1108/03068291311305017.

ESRI, 2013. World Cities [Online]. Arcgis.com. Available from: https://hub.arcgis.com/datasets/esri::world-cities/explore.

Ferraro, P.J. and Hanauer, M.M., 2011. Protecting Ecosystems and Alleviating Poverty with Parks and Reserves: 'Win-Win' or Tradeoffs? Environmental & resource economics [Online], 48(2), pp.269–286. Available from: https://doi.org/10.1007/s10640-010-9408-z.

Ferraro, P.J., Hanauer, M.M. and Sims, K.R.E., 2011. Conditions associated with protected area success in conservation and poverty reduction. *Proceedings of the National Academy of Sciences - PNAS* [Online], 108(34), pp.13913–13918. Available from: https://doi.org/10.1073/pnas.1011529108.

Fisher, J.A., Patenaude, G., Giri, K., Lewis, K., Meir, P., Pinho, P., Rounsevell, M.D.A. and Williams, M., 2014. Understanding the relationships between ecosystem services and poverty alleviation: A conceptual framework. Ecosystem services [Online], 7, pp.34–45. Available from: https://doi.org/10.1016/j.ecoser.2013.08.002.

Fotso, J.-C., 2006. Child health inequities in developing countries: differences across urban and rural areas. International journal for equity in health [Online], 5(1), pp.9–9. Available from: https://doi.org/10.1186/1475-9276-5-9.

Geldmann, J., Manica, A., Burgess, N.D., Coad, L. and Balmford, A., 2019. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. Proceedings of the National Academy of Sciences - PNAS [Online], 116(46), pp.23209–23215. Available from: https://doi.org/10.1073/pnas.1908221116.

Godwin, A., Benedict, B., Rohde, J., Thielmeyer, A., Perkins, H., Major, J., Clements, H. and Chen, Z., 2021. New Epistemological Perspectives on Quantitative Methods: An Example Using Topological Data Analysis [Online]. Studies in Engineering Education, 2(1), p.16. Available from: https://doi.org/10.21061/see.18.

Gomila, R., 2021. Logistic or Linear? Estimating Causal Effects of Experimental Treatments on Binary Outcomes Using Regression Analysis. Journal of experimental psychology. General [Online], 150(4), pp.700–709. Available from: https://doi.org/10.1037/xge0000920.

Grosh, M.E. and Glewwe, P., 1995. A guide to living standards measurement study surveys and their data sets. Washington, D.C.: World Bank.

Grosh, M.E. and Glewwe, P., 1998. Data Watch: The World Bank's Living Standards Measurement Study Household Surveys. The Journal of economic perspectives [Online], 12(1), pp.187–196. Available from: https://doi.org/10.1257/jep.12.1.187.

Hagenaars, A. and de Vos, K., 1988. The Definition and Measurement of Poverty. The Journal of human resources [Online], 23(2), pp.211–221. Available from: https://doi.org/10.2307/145776.

Ingham, K. and Lyons, M., 2024. Uganda - Economy [Online]. *Encyclopædia Britannica*. Available from: https://www.britannica.com/place/Uganda/Economy.

Jones, J.S. and Goldring, J., 2021. Exploratory and descriptive statistics. London: SAGE Publications Ltd.

Joppa, L.N., Loarie, S.R. and Pimm, S.L., 2008. On the protection of 'protected areas' [Online]. Proceedings of the National Academy of Sciences, 105(18), pp.6673–6678. Available from: https://doi.org/10.1073/pnas.0802471105.

Joppa, L.N. and Pfaff, A., 2009. High and far: biases in the location of protected areas. PloS one [Online], 4(12), pp.e8273–e8273. Available from: https://doi.org/10.1371/journal.pone.0008273.

Konkel, R., 2014. The monetization of global poverty: the concept of poverty in World Bank history, 1944–90. Journal of global history [Online], 9(2), pp.276–300. Available from: https://doi.org/10.1017/S1740022814000072.

LaValley, M.P., 2008. Logistic Regression. Circulation (New York, N.Y.) [Online], 117(18), pp.2395–2399. Available from: https://doi.org/10.1161/CIRCULATIONAHA.106.682658.

Leroux, S.J., Krawchuk, M.A., Schmiegelow, F., Cumming, S.G., Lisgo, K., Anderson, L.G. and Petkova, M., 2010. Global protected areas and IUCN designations: Do the categories match the conditions? Biological conservation [Online], 143(3), pp.609–616. Available from: https://doi.org/10.1016/j.biocon.2009.11.018.

Locke, H. and Dearden, P., 2005. Rethinking protected area categories and the new paradigm [Online]. Environmental Conservation, 32(1), pp.1–10. Available from: https://doi.org/10.1017/s0376892905001852.

Luft, J.A., Jeong, S., Idsardi, R. and Gardner, G., 2022. Literature Reviews, Theoretical Frameworks, and Conceptual Frameworks: An Introduction for New Biology Education Researchers. CBE life sciences education [Online], 21(3), pp.rm33–rm33. Available from: https://doi.org/10.1187/cbe.21-05-0134.

Lukman, A.F., Suleiman, M., Olaluwoye, O. and Farghali, R.A., 2025. Handling Multicollinearity and Outliers in Logistic Regression Using the Robust Kibria–Lukman Estimator. Axioms [Online], 14(1), pp.19-. Available from: https://doi.org/10.3390/axioms14010019.

Miranda, J.J., Corral, L., Blackman, A., Asner, G. and Lima, E., 2016. Effects of Protected Areas on Forest Cover Change and Local Communities: Evidence from the Peruvian Amazon. World development [Online], 78, pp.288–307. Available from: https://doi.org/10.1016/j.worlddev.2015.10.026.

Mammides, C., 2020. Evidence from eleven countries in four continents suggests that protected areas are not associated with higher poverty rates. *Biological conservation* [Online], 241, pp.108353-. Available from: https://doi.org/10.1016/j.biocon.2019.108353.

Mbeche, R., 2017. Climbing the Ladder of Participation: Symbolic or Substantive Representation in Preparing Uganda for REDD+? *Conservation and society* [Online], 15(4), pp.426–438. Available from: https://doi.org/10.4103/cs.cs_16_100.

Mengistu, Y.A., Mekonen, B.S. and Aynalem, N.A., 2025. Analyzing Multidimensional Poverty and Its Determinants in Ethiopia: A Micro-level Analysis at Debre Tabor City Administration [version 1; peer review: awaiting peer review]. F1000 research [Online], 14, pp.203-. Available from: https://doi.org/10.12688/f1000research.159139.1.

Michler, J.D., Josephson, A., Kilic, T. and Murray, S., 2022. Privacy protection, measurement error, and the integration of remote sensing and socioeconomic survey data. Journal of development economics [Online], 158, pp.102927-. Available from: https://doi.org/10.1016/j.jdeveco.2022.102927.

Mu, H., Li, X., Wen, Y., Huang, J., Du, P., Su, W., Miao, S. and Geng, M., 2022. A global record of annual terrestrial Human Footprint dataset from 2000 to 2018. Scientific data [Online], 9(1), pp.176–9. Available from: https://doi.org/10.1038/s41597-022-01284-8.

Naidoo, R., Gerkey, D., Hole, D., Pfaff, A., Ellis, A.M., Golden, C.D., Herrera, D., Johnson, K., Mulligan, M., Ricketts, T.H. and Fisher, B., 2019. Evaluating the impacts of protected areas on human well-being across the developing world. *Science advances* [Online], 5(4), pp.eaav3006–eaav3006. Available from: https://doi.org/10.1126/sciadv.aav3006.

Naughton-Treves, L., Alix-Garcia, J. and Chapman, C.A., 2011. Lessons about parks and poverty from a decade of forest loss and economic growth around Kibale National Park, Uganda. Proceedings of the National Academy of Sciences - PNAS [Online], 108(34), pp.13919–13924. Available from: https://doi.org/10.1073/pnas.1013332108.

Nkengne, C.T., 2016. Uganda - Poverty assessment report 2016 (Vol. 1 of 2) : Main report [Online]. World Bank. Washington, D.C.: World Bank Group. Available from: http://documents.worldbank.org/curated/en/694751474349535432.

OECD, 2023. *Pensions at a Glance 2023: OECD and G20 Indicators*. OECD Publishing. Paris. Available from: https://doi.org/10.1787/678055dd-en.

Ogwumike, F.O. and Ozughalu, U.M., 2016. Analysis of energy poverty and its implications for sustainable development in Nigeria. Environment and development economics [Online], 21(3), pp.273–290. Available from: https://doi.org/10.1017/S1355770X15000236.

Oldekop, J.A., Holmes, G., Harris, W.E. and Evans, K.L., 2016. Global Assessment of the Social and Conservation Outcomes of Protected Areas. Conservation biology [Online], 30(1), pp.133–141. Available from: https://doi.org/10.1111/cobi.12568.

Oxford Poverty and Human Development Initiative and United Nations Development Programme, 2024. Global Multidimensional Poverty Index 2024: Poverty amid conflict | OPHI. Oxford Poverty and Human Development Initiative.

Protected Planet, 2024. *Uganda* [Online]. *Protected Planet*. Available from: https://www.protectedplanet.net/country/UGA.

Pullin, A.S., Bangpan, M., Dalrymple, S., Dickson, K., Haddaway, N.R., Healey, J.R., Hauari, H., Hockley, N., Jones, J.P.G., Knight, T., Vigurs, C. and Oliver, S., 2013. Human well-being impacts of terrestrial protected areas. *Environmental evidence* [Online], 2(1), pp.19–19. Available from: https://doi.org/10.1186/2047-2382-2-19.

Putri, A.M.R., Shafiai, M.H.M. and Ismail, A.G., 2024. A Systematic Review on Multidimensional Poverty Measurement. *Journal of Ecohumanism* [Online], 3(8). Available from: https://doi.org/10.62754/joe.v3i8.5041.

Qin, S., Golden Kroner, R.E., Cook, C., Tesfaw, A.T., Braybrook, R., Rodriguez, C.M., Poelking, C. and Mascia, M.B., 2019. Protected area downgrading, downsizing, and degazettement as a threat to iconic protected areas. *Conservation biology* [Online], 33(6), pp.1275–1285. Available from: https://doi.org/10.1111/cobi.13365.

Ravallion, M., 2011. On multidimensional indices of poverty. Journal of economic inequality [Online], 9(2), pp.235–248. Available from: https://doi.org/10.1007/s10888-011-9173-4.

Roe, D. and Elliott, J., 2004. Poverty reduction and biodiversity conservation: rebuilding the bridges. *Oryx* [Online], 38(2), pp.137–139. Available from: https://doi.org/10.1017/S0030605304000249.

Rowntree, B.S., 2000. *Poverty : a study of town life*. Bristol: Policy Press.

Sacherer, A.-K., Hoch, S., Dalfiume, S. and Kassaye, R., 2022. Financing forest conservation and restoration through climate policy instruments : lessons from the CDM and REDD. Handbook of International Climate Finance [Online]. Cheltenham, UK: Edward Elgar Publishing, pp.293–317. Available from: https://doi.org/10.4337/9781784715656.00020.

Saunders, P., 2011. Down and out: poverty and exclusion in Australia. Bristol: Policy.

Savela, T., 2018. The advantages and disadvantages of quantitative methods in schoolscape research. Linguistics and education [Online], 44, pp.31–44. Available from: https://doi.org/10.1016/j.linged.2017.09.004.

Schultz, T.W., 1961. Investment in Human Capital. The American economic review, 51(1), pp.1–17.

Scott, K., Steele, D. and Temesgen, T., 2005. Chapter XXIII: Living Standards Measurement Study Surveys. Household sample surveys in developing and transition countries.

Sen, A., 1999. Commodities and capabilities. Oxford: Oxford University Press.

Sen, A., 2006. Inequality reexamined. New York: Russell Sage Foundation.

Ssewanyana, S. and Kasirye, I., 2020. Estimating Catastrophic Health Expenditures from Household Surveys: Evidence from Living Standard Measurement Surveys (LSMS)-Integrated Surveys on Agriculture (ISA) from Sub-Saharan Africa. Applied health economics and health policy [Online], 18(6), pp.781–788. Available from: https://doi.org/10.1007/s40258-020-00609-1.

Tumusiime, D.M., Vedeld, P. and Gombya-Ssembajjwe, W., 2011. Breaking the law? Illegal livelihoods from a Protected Area in Uganda. Forest policy and economics [Online], 13(4), pp.273–283. Available from: https://doi.org/10.1016/j.forpol.2011.02.001.

Turner, W.R., Brandon, K., Brooks, T.M., Gascon, C., Gibbs, H.K., Lawrence, K.S., Mittermeier, R.A. and Selig, E.R., 2012. Global Biodiversity Conservation and the Alleviation of Poverty. *Bioscience* [Online], 62(1), pp.85–92. Available from: https://doi.org/10.1525/bio.2012.62.1.13.

Uganda Bureau of Statistics, 2019. The Uganda National Panel Survey 2015/16: Basic Information Document (BID) [Online]. World Bank. Washington, D.C.: World Bank. Available from: https://microdata.worldbank.org/index.php/catalog/3460/download/46598.

Uganda Bureau of Statistics, 2021. The Uganda National Survey Report [Online]. Uganda Bureau of Statistics. Uganda Bureau of Statistics. Available from: https://www.ubos.org/wp-content/uploads/publications/09_2021Uganda-National-Survey-Report-2019-2020.pdf.

Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., Possingham, H.P., Laurance, W.F., Wood, P., Fekete, B.M., Levy, M.A. and Watson, J.E.M., 2016. Global terrestrial Human Footprint maps for 1993 and 2009. Scientific data [Online], 3(1), pp.160067–160067. Available from: https://doi.org/10.1038/sdata.2016.67.

Wang, Q., Shu, L. and Lu, X., 2023. Dynamics of multidimensional poverty and its determinants among the middle-aged and older adults in China. Humanities & social sciences communications [Online], 10(1), pp.116–9. Available from: https://doi.org/10.1057/s41599-023-01601-5.

West, P. and Brockington, D., 2006. An Anthropological Perspective on Some Unexpected Consequences of Protected Areas. *Conservation biology* [Online], 20(3), pp.609–616. Available from: https://doi.org/10.1111/j.1523-1739.2006.00432.x.

White, R., 2020. Identifying the Determinants of Multidimensional Poverty. Multidimensional Poverty in America [Online]. Cham: Springer International Publishing, pp.173–201. Available from: https://doi.org/10.1007/978-3-030-45916-1_7.

Wooldridge, J.M., 2020. *Introductory econometrics a modern approach*. Seventh edition. Australia: Cengage.

World Bank, 2016. The Uganda Poverty Assessment Report 2016: Farms, Cities and Good Fortune - Assessing Poverty Reduction in Uganda from 2006 to 2013 [Online]. World Bank. World Bank. Available from: http://hdl.handle.net/10986/26075.

World Bank, 2020. Poverty and Shared Prosperity 2020: Reversals of Fortune [Online]. World Bank. Washington, D.C.: World Bank. Available from: http://hdl.handle.net/10986/34496.

World Bank, 2024. Uganda Poverty and Equity Brief : October 2024 [Online]. Worldbank.org. Washington, D.C.: World Bank Group. Available from: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099847201032542925.

Xiao, X., Ender, P.B., Mitchell, M. and Wells, C., 2003. Regression with Stata [Online]. University of California Los Angeles. Available from: https://stats.oarc.ucla.edu/stata/webbooks/reg/.

Żogała-Siudem, B. and Jaroszewicz, S., 2021. Fast stepwise regression based on multidimensional indexes. Information sciences [Online], 549, pp.288–309. Available from: https://doi.org/10.1016/j.ins.2020.11.031.

7 APPENDIX

Appendix 1: World Bank Multidimensional Poverty Measure

Dimension	Indicator	Deprived if:	LSMS Indicator Name	LSMS Indicator Code	Weight
Monetary **(weight 0.33)**	1. Daily consumption	Daily consumption or income is less than $2.15 per person	'Monthly household expenditures in nominal prices', 'Count of Usual Members Present/Absent'	nrrexp30 & hsize in pov2015_19	1/3
Education **(weight 0.33)**	1. School attendance	At least one school-age child up to the age of grade 8 is not enrolled in school.	'Has [NAME] ever attended any formal school?'	h4q5 in gsec4	0.166
	2. Years of schooling	No adult in the household (age of grade 9 or above) has completed primary education.	'What was the highest grade/class that [NAME] completed?'	h4q7 in gsec4	0.166
Access to basic infrastructure **(weight 0.33)**	1. Electricity	The household has no access to electricity.	'Does this house have electricity?'	h10q1 in gsec10_1	0.11
	2. Source of water	The household has no access to clean water	'What is the main source of water for drinking for your household?'	h9q7 in gsec9	0.11
	3. Sanitation	The household does not have access to improved sanitation (flush toilet or similar)	'What type of toilet is mainly used in your household?'	h9q22 in gsec9	0.11

Source: World Bank (2020)
Notes: All data obtained from UNPS 2015-2016 (UBOS, 2019)

Appendix 2: Sources for World Database on Protected Areas – Uganda

Uganda Wildlife Authority's protected areas	Updated: 2020	Uganda Wildlife Authority - faciliated by the Regional Centre For Mapping Of Resources For Development (RCMRD)
UNESCO-MAB Biosphere Reserve	Updated: 2020	UNESCO-MAB
Forest Reserves of Uganda	Updated: 2021	National Forestry Authority - faciliated by the Regional Centre For Mapping Of Resources For Development (RCMRD)
UNESCO World Heritage Sites	Updated: 2024	IUCN World Heritage Programme
Ramsar Wetlands of International Importance	Updated: 2023	Ramsar Secretariat, on behalf of Ramsar Contracting Parties

Source: Protected Planet (2024)

Appendix 3: Designations distribution for World Database on Protected Areas – Uganda

Designation type	Number of observations	Share of total observations
National designations		
Forest Reserve	661	93.0%
Wildlife Sanctuary	7	1.0%

National Park	10	1.4%
Wildlife Reserve	12	1.7%
Community Wildlife Management Area	5	0.7%
International designations		
Ramsar Site, Wetland of International Importance	12	1.7%
UNESCO-MAB Biosphere Reserve	2	0.3%
World Heritage Site (natural or mixed)	2	0.3%

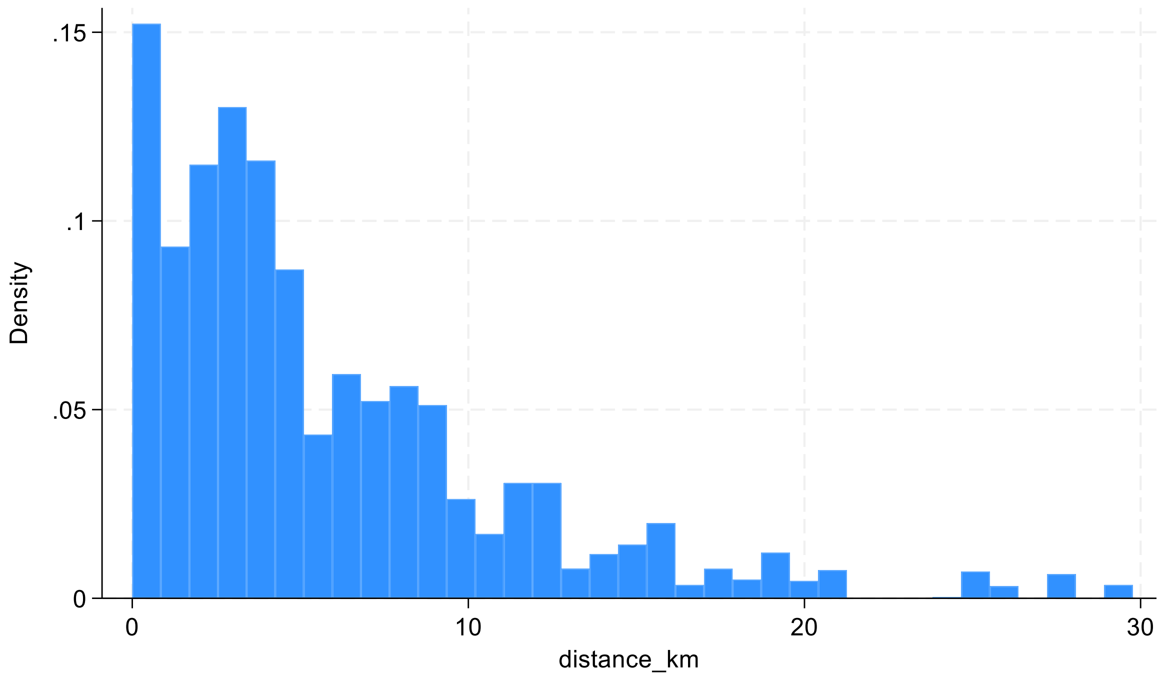
Source: Protected Planet (2024)

Appendix 4: IUCN Management Categories distribution for World Database on Protected Areas – Uganda

Category	**Number of observations**	**Share of total observations**
Not Reported	673	94.66%
Protected area with sustainable use of natural resources (VI)	12	1.69%
Natural monument or feature (III)	11	1.55%
National park (II)	10	1.41%
Not Applicable	4	0.56%
Habitat/species management area (IV)	1	0.14%

Source: Protected Planet (2024)

Appendix 5: Histogram of household distance from PAs



Data source: UNPS, WDPA

Appendix 6: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results

Do-file:

```
logistic mpi_status i.protected_status
eststo var1
logistic mpi_status i.protected_status head_sex
eststo var2
logistic mpi_status i.protected_status head_sex head_age
eststo var3
logistic mpi_status i.protected_status head_sex head_age marital_status
eststo var4
logistic mpi_status i.protected_status head_sex head_age marital_status hsize
eststo var5
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
eststo var6
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban
eststo var7
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km
eststo var8
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km hfi_2016
eststo var9
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km hfi_2016 elevation_km
eststo var10
```

logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o
eststo var11
esttab var1 var2 var3 var4 var5 var6 var7 var8 var9 var10 var11 using "nested_logistic_v3.rtf", replace eform se star(* 0.1 ** 0.05 *** 0.01) label stats(N r2_p ll, fmt(0 3 2)) title("Logistic Regressions of MPI Status (Odds Ratios) robustness check v2")

Table 9: Column (1)

```
. logistic mpi_status i.protected_status

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(3)    =  16.37
                                                        Prob > chi2   = 0.0010
Log likelihood = -1757.6373                             Pseudo R2     = 0.0046

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
              1  |        .94   .1997549    -0.29   0.771     .6197879    1.425649
              2  |   .6160074   .1132255    -2.64   0.008     .4296654    .8831641
              3  |   .6195351   .1081122    -2.74   0.006     .4400749    .8721781
                 |
           _cons |   3.361702   .5585457     7.30   0.000      2.42735    4.655712
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var1
```

```
.
. logistic mpi_status i.protected_status head_sex

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(4)    =  16.50
                                                        Prob > chi2   = 0.0024
Log likelihood = -1757.5753                             Pseudo R2     = 0.0047

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
              1  |   .9394841   .1996544    -0.29   0.769     .6194359    1.424894
              2  |   .6149461   .1130738    -2.64   0.008      .428866    .8817643
              3  |    .619298   .1080753    -2.75   0.006     .4399004    .8718566
                 |
        head_sex |   .9695121   .0851255    -0.35   0.724     .8162358    1.151571
           _cons |   3.396601   .5731517     7.25   0.000     2.440116    4.728013
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var2
```

```
. logistic mpi_status i.protected_status head_sex head_age

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(5)    =  16.95
                                                        Prob > chi2   = 0.0046
Log likelihood = -1757.3482                             Pseudo R2     = 0.0048

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
              1  |   .9370358   .1991808    -0.31   0.760     .6177614    1.421319
              2  |   .6144048   .1129853    -2.65   0.008     .4284734    .8810193
              3  |   .6185605   .1079601    -2.75   0.006     .4393577    .8708555
                 |
        head_sex |   .9643952   .0850225    -0.41   0.681     .8113567      1.1463
        head_age |    1.00191   .0028393     0.67   0.501     .9963601     1.00749
           _cons |   3.133599   .6478018     5.53   0.000     2.089664    4.699054
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var3
```

```
. logistic mpi_status i.protected_status head_sex head_age marital_status

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(6)    =  34.00
                                                        Prob > chi2   = 0.0000
Log likelihood = -1748.8239                             Pseudo R2     = 0.0096

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
              1  |   .9398306   .2002431    -0.29   0.771     .6189992    1.426951
              2  |   .6319461    .116569    -2.49   0.013     .4402173    .9071789
              3  |   .6320741    .110639    -2.62   0.009     .4485105    .8907653
                 |
        head_sex |    1.23438    .133135     1.95   0.051     .9991759    1.524951
        head_age |   1.003079   .0028602     1.08   0.281     .9974884      1.0087
  marital_status |   .6285642   .0706123    -4.13   0.000     .5043436    .7833805
           _cons |   3.054314   .6326266     5.39   0.000     2.035204    4.583733
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var4
```

```
.
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(7)    = 230.26
                                                        Prob > chi2   = 0.0000
Log likelihood = -1650.694                              Pseudo R2     = 0.0652

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
               1 |    .882258   .1937378   -0.57   0.568     .5736904    1.356793
               2 |   .6384467   .1213606   -2.36   0.018     .4398677    .9266745
               3 |    .631695   .1139523   -2.55   0.011     .4435658    .8996154
                 |
        head_sex |   1.195543   .1300739    1.64   0.101     .9659517    1.479705
        head_age |   .9923372   .0029272   -2.61   0.009     .9866164    .9980911
  marital_status |   1.000657   .1190148    0.01   0.996     .7925856    1.263352
           hsize |   1.297754   .0261957   12.91   0.000     1.247414    1.350126
           _cons |    1.23762   .2732933    0.97   0.334     .8028297     1.90788
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var5
```

Table 9: Column (2)

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(8)    = 265.32
                                                        Prob > chi2   = 0.0000
Log likelihood = -1633.1634                             Pseudo R2     = 0.0751

----------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+----------------------------------------------------------------
protected_status |
               1 |   .8370667   .1853394   -0.80   0.422     .5423643    1.291901
               2 |   .6166528   .1182522   -2.52   0.012     .4234581     .897989
               3 |    .616146   .1120914   -2.66   0.008     .4313503    .8801104
                 |
        head_sex |   1.125828   .1237446    1.08   0.281     .9076381    1.396469
        head_age |   .9904014   .0029671   -3.22   0.001      .984603     .996234
  marital_status |   1.078468   .1301953    0.63   0.531     .8512328    1.366364
           hsize |   1.274049   .0258842   11.92   0.000     1.224313    1.325804
    working_rate |    .476765   .0596009   -5.93   0.000     .3731596    .6091356
           _cons |   1.795157   .4160485    2.52   0.012     1.139794    2.827342
----------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var6
```

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(9)    = 657.83
                                                        Prob > chi2   = 0.0000
Log likelihood = -1436.9088                             Pseudo R2     = 0.1863
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.6318727	.1499411	-1.93	0.053	.3968648	1.006043
2	.6477376	.1349634	-2.08	0.037	.430568	.9744431
3	.7168839	.1417036	-1.68	0.092	.4866259	1.056094
head_sex	1.110533	.1335467	0.87	0.383	.8773454	1.405699
head_age	.9867889	.0032132	-4.08	0.000	.9805112	.9931068
marital_status	1.270106	.1680331	1.81	0.071	.9800028	1.646086
hsize	1.271153	.027563	11.06	0.000	1.218263	1.32634
working_rate	.6174996	.0843812	-3.53	0.000	.4724112	.807148
urban	6.844701	.6893038	19.10	0.000	5.618666	8.338266
_cons	.4754196	.123625	-2.86	0.004	.2855855	.79144

```
Note: _cons estimates baseline odds.

.
. eststo var7
```

```
.
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(10)   = 748.42
                                                        Prob > chi2   = 0.0000
Log likelihood = -1391.6145                             Pseudo R2     = 0.2119
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.796493	.1904784	-0.95	0.341	.4984484	1.272752
2	.7468534	.1570968	-1.39	0.165	.4945264	1.127928
3	.8160696	.1615872	-1.03	0.305	.553584	1.203014
head_sex	1.124657	.1381834	0.96	0.339	.8839652	1.430885
head_age	.9878123	.0032725	-3.70	0.000	.9814191	.9942471
marital_status	1.313173	.177694	2.01	0.044	1.007257	1.711999
hsize	1.277469	.0282079	11.09	0.000	1.223362	1.333969
working_rate	.6974328	.0976387	-2.57	0.010	.530074	.9176314
urban	5.714189	.5932105	16.79	0.000	4.662172	7.003593
distance_from_nearest_city_km	1.012809	.001404	9.18	0.000	1.010061	1.015565
_cons	.2221278	.0613702	-5.45	0.000	.1292499	.3817471

```
Note: _cons estimates baseline odds.

.
. eststo var8
```

```
.
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(11)   = 821.33
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.9837                             Pseudo R2     = 0.2327
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.8018999	.1904146	-0.93	0.353	.5034991	1.277149
2	.9256065	.1956279	-0.37	0.715	.6116796	1.400647
3	.9551005	.1881836	-0.23	0.816	.6491376	1.405275
head_sex	1.153705	.1439651	1.15	0.252	.9033945	1.47337
head_age	.9878457	.0033109	-3.65	0.000	.9813777	.9943563
marital_status	1.290244	.1778819	1.85	0.065	.9847347	1.690535
hsize	1.279458	.0286107	11.02	0.000	1.224593	1.336781
working_rate	.7586579	.1078368	-1.94	0.052	.574189	1.002391
urban	3.565467	.4173137	10.86	0.000	2.834583	4.484808
distance_from_nearest_city_km	1.006635	.0015548	4.28	0.000	1.003592	1.009687
hfi_2016	.9284478	.00823	-8.38	0.000	.9124566	.9447193
_cons	2.029044	.7665565	1.87	0.061	.9676409	4.254696

```
Note: _cons estimates baseline odds.

.
. eststo var9
```

```
.
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(12)   = 822.42
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.4365                             Pseudo R2     = 0.2330
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.8059282	.1914603	-0.91	0.364	.5059186	1.283843
2	.9249974	.1954588	-0.37	0.712	.6113295	1.399606
3	.9497169	.1871835	-0.26	0.794	.6453978	1.397529
head_sex	1.1516	.1436368	1.13	0.258	.9018471	1.470518
head_age	.9879717	.0033126	-3.61	0.000	.9815005	.9944856
marital_status	1.295372	.1786333	1.88	0.061	.9885824	1.697369
hsize	1.278763	.0286177	10.99	0.000	1.223886	1.336101
working_rate	.7651468	.1088842	-1.88	0.060	.5789147	1.011288
urban	3.579812	.4195885	10.88	0.000	2.845058	4.50432
distance_from_nearest_city_km	1.006629	.0015526	4.28	0.000	1.003591	1.009677
hfi_2016	.928243	.0082411	-8.39	0.000	.9122305	.9445366
elevation_km	.999777	.0002122	-1.05	0.293	.9993611	1.000193
_cons	2.676022	1.231934	2.14	0.033	1.085502	6.597036

```
Note: _cons estimates baseline odds.

.
. eststo var10
```

Table 9: Column (3)

```
.
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(13)   = 823.07
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.1107                             Pseudo R2     = 0.2332
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.8057675	.1914166	-0.91	0.363	.5058245	1.28357
2	.9221279	.1949112	-0.38	0.701	.6093569	1.395438
3	.9536139	.187985	-0.24	0.810	.6480015	1.40336
head_sex	1.152838	.1438634	1.14	0.254	.9027063	1.47228
head_age	.9879519	.0033138	-3.61	0.000	.9814784	.9944682
marital_status	1.292922	.1783382	1.86	0.063	.9866489	1.694269
hsize	1.278402	.0286082	10.98	0.000	1.223543	1.335721
working_rate	.7663618	.1090561	-1.87	0.061	.5798355	1.012892
urban	3.608241	.424383	10.91	0.000	2.865376	4.543699
distance_from_nearest_city_km	1.006644	.001554	4.29	0.000	1.003603	1.009695
hfi_2016	.9284625	.0082467	-8.36	0.000	.9124391	.9447672
elevation_km	.9999259	.0002815	-0.26	0.792	.9993744	1.000478
slope_o	.981523	.0225872	-0.81	0.418	.9382364	1.026807
_cons	2.326913	1.14489	1.72	0.086	.8870972	6.103644

```
Note: _cons estimates baseline odds.

.
. eststo var11
```

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 7: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results – Alternative PA categories (5km, 10km, >10km)

Do-file:

```
logistic mpi_status i.protected_status_v2
eststo var1p2
logistic mpi_status i.protected_status_v2 head_sex
eststo var2p2
logistic mpi_status i.protected_status_v2 head_sex head_age
eststo var3p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status
eststo var4p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize
eststo var5p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate
eststo var6p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban
eststo var7p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km
eststo var8p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km hfi_2016
eststo var9p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km hfi_2016 elevation_km
eststo var10p2
logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban
distance_from_nearest_city_km hfi_2016 elevation_km slope_o
eststo var11p2
esttab var1p2 var2p2 var3p2 var4p2 var5p2 var6p2 var7p2 var8p2 var9p2 var10p2 var11p2 using
"nested_logistic_protectedv2.rtf", replace eform se star(* 0.1 ** 0.05 *** 0.01) label stats(N r2_p ll, fmt(0 3
2)) title("Logistic Regressions of MPI Status (Odds Ratios) robustness check protectected v2")
```

```
. logistic mpi_status i.protected_status_v2

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(2)    =  16.29
                                                        Prob > chi2   = 0.0003
Log likelihood = -1757.6798                             Pseudo R2     = 0.0046

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v2 |
                  1 |   .6395992   .0831654    -3.44   0.001     .4957109    .8252535
                  2 |   .6432619   .0749471    -3.79   0.000     .5119335    .8082806
                    |
              _cons |   3.237705   .3353544    11.34   0.000     2.642845    3.966458
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var1p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(3)    =  16.41
                                                        Prob > chi2   = 0.0009
Log likelihood = -1757.6185                             Pseudo R2     = 0.0046

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v2 |
                  1 |   .6387144   .0830915    -3.45   0.001     .4949626    .8242159
                  2 |   .6432292   .0749448    -3.79   0.000     .5119049    .8082433
                    |
           head_sex |   .9696965   .0851379    -0.35   0.726     .8163974    1.151781
              _cons |   3.270031   .3512978    11.03   0.000     2.649157    4.036417
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var2p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(4)    =  16.86
                                                        Prob > chi2   = 0.0021
Log likelihood = -1757.3951                             Pseudo R2     = 0.0048
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.6391543	.0831569	-3.44	0.001	.4952911	.8248044
2	.6434736	.074979	-3.78	0.000	.5120905	.8085646
head_sex	.9646277	.0850381	-0.41	0.683	.8115604	1.146565
head_age	1.001894	.0028386	0.67	0.504	.9963455	1.007473
_cons	3.014137	.4894016	6.80	0.000	2.192575	4.14354

```
Note: _cons estimates baseline odds.

.
. eststo var3p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(5)    =  33.91
                                                        Prob > chi2   = 0.0000
Log likelihood = -1748.8665                             Pseudo R2     = 0.0096
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.6562298	.0856844	-3.23	0.001	.5080588	.8476136
2	.6563609	.076726	-3.60	0.000	.5219641	.8253626
head_sex	1.234613	.1331385	1.95	0.051	.9993985	1.525186
head_age	1.003065	.0028597	1.07	0.283	.9974756	1.008685
marital_status	.6285254	.0705995	-4.13	0.000	.5043257	.7833117
_cons	2.942948	.478323	6.64	0.000	2.140106	4.04697

```
Note: _cons estimates baseline odds.

.
. eststo var4p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize

Logistic regression                                 Number of obs =  2,857
                                                    LR chi2(6)    = 229.93
                                                    Prob > chi2   = 0.0000
Log likelihood = -1650.8575                         Pseudo R2     = 0.0651
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.6886211	.0927514	-2.77	0.006	.5288477	.8966645
2	.6813388	.0821842	-3.18	0.001	.5378855	.8630508
head_sex	1.196262	.1301068	1.65	0.099	.9666045	1.480485
head_age	.992306	.0029265	-2.62	0.009	.9865866	.9980585
marital_status	1.000027	.1189061	0.00	1.000	.7921394	1.262473
hsize	1.297434	.0261785	12.91	0.000	1.247126	1.349771
_cons	1.150284	.2055056	0.78	0.433	.8104613	1.632592

```
Note: _cons estimates baseline odds.

.
. eststo var5p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate

Logistic regression                                 Number of obs =  2,857
                                                    LR chi2(7)    = 264.67
                                                    Prob > chi2   = 0.0000
Log likelihood = -1633.4879                         Pseudo R2     = 0.0749
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.686375	.0931536	-2.77	0.006	.5260631	.8955401
2	.6857831	.0833048	-3.11	0.002	.5404903	.8701331
head_sex	1.126694	.1237708	1.09	0.278	.9084451	1.397375
head_age	.9903747	.0029663	-3.23	0.001	.9845778	.9962057
marital_status	1.077205	.1299704	0.62	0.538	.8503471	1.364583
hsize	1.273733	.0258688	11.91	0.000	1.224027	1.325457
working_rate	.4787898	.0597792	-5.90	0.000	.3748594	.6115352
_cons	1.61504	.3056573	2.53	0.011	1.114519	2.34034

```
Note: _cons estimates baseline odds.

.
. eststo var6p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(8)    = 654.03
                                                        Prob > chi2   = 0.0000
Log likelihood = -1438.8092                             Pseudo R2     = 0.1852
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.8556203	.1248751	-1.07	0.285	.6427631	1.138967
2	.9459821	.1238787	-0.42	0.672	.7318397	1.222784
head_sex	1.114365	.1337564	0.90	0.367	.8807612	1.409927
head_age	.9867232	.0032093	-4.11	0.000	.9804531	.9930335
marital_status	1.263825	.1668709	1.77	0.076	.9756578	1.637105
hsize	1.270057	.0275139	11.04	0.000	1.21726	1.325145
working_rate	.6234598	.0849858	-3.47	0.001	.4772856	.8144014
urban	6.754318	.6776394	19.04	0.000	5.548596	8.222045
_cons	.365005	.0800409	-4.60	0.000	.2374878	.5609915

```
Note: _cons estimates baseline odds.

.
. eststo var7p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(9)    = 747.51
                                                        Prob > chi2   = 0.0000
Log likelihood = -1392.0704                             Pseudo R2     = 0.2117
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v2						
1	.8583702	.1277665	-1.03	0.305	.6411728	1.149143
2	.9373529	.1233394	-0.49	0.623	.7242687	1.213128
head_sex	1.127	.138358	0.97	0.330	.885982	1.433584
head_age	.9877827	.0032716	-3.71	0.000	.9813911	.9942158
marital_status	1.31041	.1771856	2.00	0.046	1.00534	1.708054
hsize	1.277048	.0281892	11.08	0.000	1.222977	1.333511
working_rate	.701734	.0980815	-2.53	0.011	.5335804	.9228798
urban	5.66604	.5856943	16.78	0.000	4.626916	6.938534
distance_from_nearest_city_km	1.012945	.001398	9.32	0.000	1.010209	1.015689
_cons	.1934381	.04529	-7.02	0.000	.12225	.3060802

```
Note: _cons estimates baseline odds.

.
. eststo var8p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(10)   = 820.46
                                                        Prob > chi2   = 0.0000
Log likelihood = -1354.4188                             Pseudo R2     = 0.2325

------------------------------------------------------------------------------------------------
                   mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
------------------------------+-----------------------------------------------------------------
          protected_status_v2 |
                            1 |   1.058297   .1613605     0.37   0.710     .7849158    1.426894
                            2 |   1.091225   .1449094     0.66   0.511     .8411604     1.41563
                              |
                     head_sex |   1.155798   .1441237     1.16   0.246     .9051913    1.475787
                     head_age |   .9878213   .0033104    -3.66   0.000     .9813544    .9943309
               marital_status |    1.28848   .1775369     1.84   0.066     .9835413    1.687963
                        hsize |   1.279105   .0285963    11.01   0.000     1.224268    1.336399
                 working_rate |   .7633041   .1083355    -1.90   0.057     .5779454    1.008111
                        urban |   3.536255   .4125677    10.83   0.000     2.813427    4.444793
distance_from_nearest_city_km |   1.006758   .0015502     4.37   0.000     1.003725    1.009801
                     hfi_2016 |   .9284688   .0082252    -8.38   0.000     .9124868    .9447307
                        _cons |    1.77483   .6188298     1.65   0.100     .8961245     3.51516
------------------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var9p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(11)   = 821.59
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.8515                             Pseudo R2     = 0.2328

------------------------------------------------------------------------------------------------
                   mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
------------------------------+-----------------------------------------------------------------
          protected_status_v2 |
                            1 |   1.054277   .1607871     0.35   0.729     .7818771    1.421579
                            2 |   1.081607   .1439417     0.59   0.556     .8332794     1.40394
                              |
                     head_sex |   1.153698   .1437976     1.15   0.251     .9036452    1.472945
                     head_age |    .987951   .0033121    -3.62   0.000     .9814807     .994464
               marital_status |    1.29369   .1783032     1.87   0.062     .9874453    1.694913
                        hsize |   1.278424   .0286037    10.98   0.000     1.223573    1.335734
                 working_rate |   .7699212   .1093956    -1.84   0.066     .5827762    1.017163
                        urban |   3.551485   .4149716    10.85   0.000     2.824566    4.465481
distance_from_nearest_city_km |   1.006749    .001548     4.37   0.000      1.00372    1.009788
                     hfi_2016 |   .9282575   .0082365    -8.39   0.000     .9122538     .944542
                 elevation_km |   .9997729   .0002122    -1.07   0.285      .999357    1.000189
                        _cons |   2.359916   1.035019     1.96   0.050     .9990196    5.574669
------------------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var10p2
```

```
. logistic mpi_status i.protected_status_v2 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(12)   = 822.24
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.5266                             Pseudo R2     = 0.2330

------------------------------------------------------------------------------------------------
                   mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
------------------------------+-----------------------------------------------------------------
          protected_status_v2 |
                            1 |   1.051083   .1604535     0.33   0.744     .7792854    1.417678
                            2 |   1.086128   .1446637     0.62   0.535     .8365799    1.410114
                              |
                     head_sex |   1.154918   .1440206     1.15   0.248      .904492     1.47468
                     head_age |   .9879316   .0033134    -3.62   0.000     .9814588    .9944471
               marital_status |   1.291159   .1779967     1.85   0.064     .9854504    1.691706
                        hsize |   1.278059    .028594    10.97   0.000     1.223226    1.335349
                 working_rate |   .7712159   .1095774    -1.83   0.067     .5837594    1.018868
                        urban |   3.579672   .4197068    10.88   0.000     2.844737    4.504476
distance_from_nearest_city_km |   1.006764   .0015494     4.38   0.000     1.003732    1.009806
                     hfi_2016 |   .9284782   .0082421    -8.36   0.000     .9124637    .9447739
                 elevation_km |   .9999219   .0002817    -0.28   0.781     .9993699    1.000474
                      slope_o |    .981551   .0225801    -0.81   0.418     .9382777     1.02682
                        _cons |   2.051521   .9679161     1.52   0.128     .8137208    5.172213
------------------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var11p2
```

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 8: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results – Alternative PA categories (5km, >5km)

Do-file:

logistic mpi_status protected_status_v3
eststo var1p3
logistic mpi_status protected_status_v3 head_sex
eststo var2p3
logistic mpi_status protected_status_v3 head_sex head_age
eststo var3p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status
eststo var4p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize
eststo var5p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate
eststo var6p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban
eststo var7p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km
eststo var8p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016
eststo var9p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km
eststo var10p3
logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o
eststo var11p3
esttab var1p3 var2p3 var3p3 var4p3 var5p3 var6p3 var7p3 var8p3 var9p3 var10p3 var11p3 using "nested_logistic_protectedv3.rtf", replace eform se star(* 0.1 ** 0.05 *** 0.01) label stats(N r2_p ll, fmt(0 3 2)) title("Logistic Regressions of MPI Status (Odds Ratios) robustness check protectected v3")

```
. logistic mpi_status protected_status_v3

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(1)    =   4.22
                                                        Prob > chi2   = 0.0400
Log likelihood = -1763.714                              Pseudo R2     = 0.0012

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v3 |   .8452182   .0693385    -2.05   0.040       .71968    .9926547
              _cons |   2.464088   .1535565    14.47   0.000     2.180777    2.784205
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var1p3
```

```
. logistic mpi_status protected_status_v3 head_sex

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(2)    =   4.28
                                                        Prob > chi2   = 0.1178
Log likelihood = -1763.6843                             Pseudo R2     = 0.0012

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v3 |   .8456662   .0694001    -2.04   0.041       .72002    .9932381
           head_sex |   .9788999   .0857211    -0.24   0.808      .824517     1.16219
              _cons |   2.479692   .1674418    13.45   0.000     2.172301    2.830579
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var2p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(3)    =   4.76
                                                        Prob > chi2   = 0.1899
Log likelihood = -1763.4408                             Pseudo R2     = 0.0013

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v3 |   .8456423   .0694042    -2.04   0.041     .7199895    .9932239
           head_sex |   .9735572    .085603    -0.30   0.761     .8194396    1.156661
           head_age |   1.001974   .0028344     0.70   0.486     .9964339    1.007545
              _cons |   2.278756   .3157146     5.94   0.000     1.736867    2.989711
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var3p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(4)    =  23.30
                                                        Prob > chi2   = 0.0001
Log likelihood = -1754.1736                             Pseudo R2     = 0.0066

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v3 |   .8493697   .0699396    -1.98   0.047     .7227804    .9981301
           head_sex |   1.256842   .1351001     2.13   0.033     1.018084    1.551593
           head_age |   1.003202   .0028563     1.12   0.261     .9976196    1.008816
     marital_status |   .6171179   .0691248    -4.31   0.000     .4954766    .7686226
              _cons |   2.259346   .3128439     5.89   0.000     1.722343    2.963778
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var4p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(5)    = 222.14
                                                        Prob > chi2   = 0.0000
Log likelihood = -1654.7523                             Pseudo R2     = 0.0629

------------------------------------------------------------------------------------
         mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
--------------------+---------------------------------------------------------------
protected_status_v3 |   .8573088   .0730265    -1.81   0.071     .7254893     1.01308
           head_sex |   1.215701   .1317762     1.80   0.072     .9830161    1.503464
           head_age |   .9923984   .0029235    -2.59   0.010      .986685     .998145
     marital_status |   .9861445   .1169475    -0.12   0.906     .7816206    1.244185
              hsize |   1.298799   .0261512    12.98   0.000     1.248542    1.351079
              _cons |   .9049585   .1405045    -0.64   0.520     .6675296    1.226837
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var5p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(6)    = 256.86
                                                        Prob > chi2   = 0.0000
Log likelihood = -1637.3914                             Pseudo R2     = 0.0727
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	.8644371	.0741876	-1.70	0.090	.7306034	1.022787
head_sex	1.14561	.1253955	1.24	0.214	.9244143	1.419735
head_age	.9904766	.0029641	-3.20	0.001	.984684	.9963032
marital_status	1.062067	.1277971	0.50	0.617	.8389338	1.344546
hsize	1.275178	.0258443	11.99	0.000	1.225517	1.326851
working_rate	.4796135	.0597593	-5.90	0.000	.3756926	.6122802
_cons	1.266506	.2108841	1.42	0.156	.9138502	1.755253

```
Note: _cons estimates baseline odds.

.
. eststo var6p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(7)    = 652.88
                                                        Prob > chi2   = 0.0000
Log likelihood = -1439.3826                             Pseudo R2     = 0.1849
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	1.041839	.0978226	0.44	0.662	.8667182	1.252344
head_sex	1.121262	.1343162	0.96	0.339	.8866285	1.417989
head_age	.986745	.0032086	-4.10	0.000	.9804763	.9930537
marital_status	1.257837	.1659194	1.74	0.082	.9712781	1.62894
hsize	1.270884	.0275188	11.07	0.000	1.218076	1.32598
working_rate	.6241131	.0850333	-3.46	0.001	.4778482	.8151483
urban	6.81714	.6816662	19.20	0.000	5.60387	8.293091
_cons	.3279131	.0639109	-5.72	0.000	.2237989	.4804627

```
Note: _cons estimates baseline odds.

.
. eststo var7p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km

Logistic regression                                     Number of obs =  2,857
                                                        LR chi2(8)    = 746.45
                                                        Prob > chi2   = 0.0000
Log likelihood = -1392.5988                             Pseudo R2     = 0.2114
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	1.027195	.0984526	0.28	0.780	.8512728	1.239474
head_sex	1.13434	.1389535	1.03	0.303	.8922231	1.442159
head_age	.9878099	.0032707	-3.70	0.000	.9814202	.9942412
marital_status	1.303595	.1760617	1.96	0.050	1.000416	1.698654
hsize	1.277528	.0281929	11.10	0.000	1.223449	1.333998
working_rate	.7025277	.0981535	-2.53	0.012	.534242	.9238231
urban	5.713899	.5886525	16.92	0.000	4.669182	6.992369
distance_from_nearest_city_km	1.012967	.0013996	9.32	0.000	1.010228	1.015714
_cons	.1747302	.0370337	-8.23	0.000	.1153341	.2647149

```
Note: _cons estimates baseline odds.

.
. eststo var8p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(9)    = 820.32
                                                        Prob > chi2   = 0.0000
Log likelihood = -1354.4878                             Pseudo R2     = 0.2324
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	1.055313	.1033539	0.55	0.583	.8709987	1.278631
head_sex	1.153339	.1436909	1.15	0.252	.9034589	1.472331
head_age	.9878119	.0033102	-3.66	0.000	.9813452	.9943212
marital_status	1.291056	.1777578	1.86	0.064	.9857076	1.690993
hsize	1.278995	.0285921	11.01	0.000	1.224165	1.33628
working_rate	.7625709	.1082181	-1.91	0.056	.5774102	1.007108
urban	3.537786	.4127629	10.83	0.000	2.814619	4.446758
distance_from_nearest_city_km	1.006795	.0015465	4.41	0.000	1.003768	1.009831
hfi_2016	.9289184	.0081407	-8.41	0.000	.9130992	.9450116
_cons	1.812098	.6237728	1.73	0.084	.9229436	3.557854

```
Note: _cons estimates baseline odds.

.
. eststo var9p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(10)   = 821.47
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.9115                             Pseudo R2     = 0.2328
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	1.048302	.1028587	0.48	0.631	.8649019	1.27059
head_sex	1.151417	.1433852	1.13	0.258	.9020554	1.469712
head_age	.9879434	.003312	-3.62	0.000	.9814733	.9944562
marital_status	1.296164	.1785024	1.88	0.060	.9895459	1.69779
hsize	1.278319	.0285995	10.98	0.000	1.223476	1.33562
working_rate	.7693267	.1093046	-1.85	0.065	.582336	1.016361
urban	3.55301	.4151619	10.85	0.000	2.82576	4.467428
distance_from_nearest_city_km	1.006784	.0015442	4.41	0.000	1.003762	1.009815
hfi_2016	.9286757	.0081523	-8.43	0.000	.9128342	.944792
elevation_km	.9997713	.000212	-1.08	0.281	.9993558	1.000187
_cons	2.410639	1.046601	2.03	0.043	1.029379	5.645328

```
Note: _cons estimates baseline odds.

.
. eststo var10p3
```

```
. logistic mpi_status protected_status_v3 head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(11)   = 822.14
                                                        Prob > chi2   = 0.0000
Log likelihood = -1353.5798                             Pseudo R2     = 0.2329
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status_v3	1.05468	.103838	0.54	0.589	.8695927	1.279161
head_sex	1.152797	.1436318	1.14	0.254	.9030217	1.47166
head_age	.9879245	.0033133	-3.62	0.000	.9814519	.9944399
marital_status	1.29346	.1781756	1.87	0.062	.9874139	1.694365
hsize	1.277954	.0285897	10.96	0.000	1.22313	1.335235
working_rate	.7706599	.1094912	-1.83	0.067	.5833492	1.018115
urban	3.581403	.4199127	10.88	0.000	2.846108	4.506661
distance_from_nearest_city_km	1.006797	.0015457	4.41	0.000	1.003772	1.009831
hfi_2016	.9288723	.0081575	-8.40	0.000	.9130207	.9449991
elevation_km	.9999219	.0002816	-0.28	0.781	.9993702	1.000474
slope_o	.9813566	.0225787	-0.82	0.413	.9380862	1.026623
_cons	2.090203	.9786139	1.57	0.115	.8349566	5.232548

```
Note: _cons estimates baseline odds.

.
. eststo var11p3
```

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 9: Household MDP and PA exposure in Uganda – Logistic Regression Analysis Results without Outliers

Do-file:

```
logistic mpi_status i.protected_status if outlier==0
eststo var1o
logistic mpi_status i.protected_status head_sex if outlier==0
eststo var2o
logistic mpi_status i.protected_status head_sex head_age if outlier==0
eststo var3o
logistic mpi_status i.protected_status head_sex head_age marital_status if outlier==0
eststo var4o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize if outlier==0
eststo var5o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate if
outlier==0
eststo var6o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
urban if outlier==0
eststo var7o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
urban distance_from_nearest_city_km if outlier==0
eststo var8o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
urban distance_from_nearest_city_km hfi_2016 if outlier==0
eststo var9o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
urban distance_from_nearest_city_km hfi_2016 elevation_km if outlier==0
eststo var10o
logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate
urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o if outlier==0
eststo var11o
esttab var1o var2o var3o var4o var5o var6o var7o var8o var9o var10o var11o using
"nested_logistic_outlier.rtf", replace eform se star(* 0.1 ** 0.05 *** 0.01) label stats(N r2_p ll,
fmt(0 3 2)) title("Logistic Regressions of MPI Status (Odds Ratios) robustness check outlier")
```

Table 10: Column (1)

```
. logistic mpi_status i.protected_status if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(3)    =  14.78
                                                        Prob > chi2   = 0.0020
Log likelihood = -1215.8336                             Pseudo R2     = 0.0060

------------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------------
protected_status |
              1  |   .9244444   .2155513    -0.34   0.736      .585339    1.460004
              2  |   1.265185   .2671943     1.11   0.265     .8363516      1.9139
              3  |   .7930029   .1527265    -1.20   0.228     .5436753    1.156671
                 |
           _cons |      3.125   .5676844     6.27   0.000     2.188878    4.461475
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var1o

. logistic mpi_status i.protected_status head_sex if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(4)    =  15.30
                                                        Prob > chi2   = 0.0041
Log likelihood = -1215.5731                             Pseudo R2     = 0.0063

------------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------------
protected_status |
              1  |   .9226443   .2151733    -0.35   0.730     .5841475    1.457291
              2  |   1.256667    .265686     1.08   0.280     .8303443    1.901876
              3  |   .7914502   .1524629    -1.21   0.225     .5425633    1.154508
                 |
        head_sex |   .9261216   .0982596    -0.72   0.469     .7522414    1.140194
           _cons |   3.211565   .5962729     6.28   0.000     2.231922    4.621196
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var2o
```

```
. logistic mpi_status i.protected_status head_sex head_age if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(5)    =  15.35
                                                        Prob > chi2   = 0.0090
Log likelihood = -1215.5523                             Pseudo R2     = 0.0063

------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------
protected_status |
               1 |   .9211753   .2149535   -0.35   0.725     .5830649    1.455351
               2 |   1.255562   .2655084    1.08   0.282     .8295412     1.90037
               3 |   .7909024   .1523824   -1.22   0.223     .5421541     1.15378
                 |
        head_sex |   .9240914   .0985504   -0.74   0.459      .749787    1.138917
        head_age |   1.000722   .0035494    0.20   0.839     .9937897    1.007703
           _cons |   3.116261   .7396719    4.79   0.000     1.957013    4.962196
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var3o
```

```
. logistic mpi_status i.protected_status head_sex head_age marital_status if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(6)    =  26.28
                                                        Prob > chi2   = 0.0002
Log likelihood = -1210.084                              Pseudo R2     = 0.0107

------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------
protected_status |
               1 |   .9169775   .2144974   -0.37   0.711     .5797589     1.45034
               2 |   1.280474   .2715009    1.17   0.244     .8450629    1.940226
               3 |   .8049596   .1555312   -1.12   0.261     .5511987    1.175547
                 |
        head_sex |   1.178116   .1545208    1.25   0.211      .911056     1.52346
        head_age |   1.002245   .0035866    0.63   0.531     .9952402    1.009299
  marital_status |   .6325968   .0872828   -3.32   0.001     .4827053    .8290332
           _cons |   2.998192   .7125623    4.62   0.000     1.881739    4.777046
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var4o
```

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(7)    = 176.12
                                                        Prob > chi2   = 0.0000
Log likelihood = -1135.1653                             Pseudo R2     = 0.0720

------------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------------
protected_status |
               1 |   .8348489   .2021977    -0.75   0.456     .5193374    1.342042
               2 |   1.295629   .2833568     1.18   0.236     .8439585    1.989025
               3 |   .8085449   .1613938    -1.06   0.287     .5467586    1.195674
                 |
        head_sex |   1.137283   .1495912     0.98   0.328     .8788338    1.471737
        head_age |    .990965   .0036311    -2.48   0.013     .9838737    .9981075
  marital_status |   1.052288    .152569     0.35   0.725     .7919923    1.398133
           hsize |   1.325947   .0329793    11.34   0.000     1.262859    1.392187
           _cons |   1.109028   .2825679     0.41   0.685     .6730789    1.827339
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var5o
```

Table 10: Column (2)

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(8)    = 189.23
                                                        Prob > chi2   = 0.0000
Log likelihood = -1128.6092                             Pseudo R2     = 0.0773

------------------------------------------------------------------------------------
      mpi_status | Odds ratio   Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------------
protected_status |
               1 |   .8117017   .1974639    -0.86   0.391     .5038757    1.307584
               2 |   1.253615   .2757726     1.03   0.304     .8145456     1.92936
               3 |   .8024469   .1609613    -1.10   0.273      .541596    1.188932
                 |
        head_sex |    1.09011   .1441893     0.65   0.514     .8411655     1.41273
        head_age |   .9895432   .0036647    -2.84   0.005     .9823866     .996752
  marital_status |   1.107025   .1618985     0.70   0.487     .8311362    1.474493
           hsize |   1.308034   .0327757    10.72   0.000     1.245347    1.373877
    working_rate |   .5730766   .0876114    -3.64   0.000     .4246996     .773292
           _cons |   1.439957   .3836427     1.37   0.171     .8542143    2.427348
------------------------------------------------------------------------------------
Note: _cons estimates baseline odds.

.
. eststo var6o
```

. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban if outlier==0

Logistic regression

Number of obs = 2,138
LR chi2(9) = 348.80
Prob > chi2 = 0.0000
Log likelihood = -1048.8265
Pseudo R2 = 0.1426

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.5858167	.1513063	-2.07	0.038	.3531109	.9718793
2	.9551646	.2239953	-0.20	0.845	.6032027	1.512492
3	.7857834	.1684385	-1.12	0.261	.5162279	1.196091
head_sex	1.06383	.1483384	0.44	0.657	.8094354	1.398177
head_age	.9855295	.0038463	-3.73	0.000	.9780198	.993097
marital_status	1.235204	.1909642	1.37	0.172	.9123087	1.672383
hsize	1.301255	.0339081	10.11	0.000	1.236465	1.369441
working_rate	.6284922	.1012651	-2.88	0.004	.4583012	.861884
urban	4.737618	.5883194	12.53	0.000	3.714134	6.04314
_cons	.5919229	.1717845	-1.81	0.071	.3351462	1.045432

Note: _cons estimates baseline odds.

.
. eststo var7o

. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km if outlier==0

Logistic regression

Number of obs = 2,138
LR chi2(10) = 380.26
Prob > chi2 = 0.0000
Log likelihood = -1033.0963
Pseudo R2 = 0.1554

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.6652651	.1738443	-1.56	0.119	.398623	1.110266
2	.9750125	.2304105	-0.11	0.915	.6135616	1.549395
3	.8463128	.1829664	-0.77	0.440	.5539972	1.292868
head_sex	1.095086	.1542921	0.64	0.519	.8308417	1.443372
head_age	.9864135	.0038832	-3.47	0.001	.9788319	.9940539
marital_status	1.260063	.1967566	1.48	0.139	.9278516	1.71122
hsize	1.306172	.0343536	10.16	0.000	1.240547	1.37527
working_rate	.6929844	.1133662	-2.24	0.025	.5028915	.9549325
urban	4.64955	.5828531	12.26	0.000	3.636696	5.944494
distance_from_nearest_city_km	1.008853	.001621	5.49	0.000	1.005681	1.012035
_cons	.3197371	.1004664	-3.63	0.000	.1727158	.5919077

Note: _cons estimates baseline odds.

.
. eststo var8o

. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 if outlier==0

Logistic regression

Number of obs = 2,138
LR chi2(11) = 407.95
Prob > chi2 = 0.0000
Log likelihood = -1019.2483
Pseudo R2 = 0.1668

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.6396414	.1676431	-1.70	0.088	.3826889	1.069122
2	.9973375	.2371986	-0.01	0.991	.6257477	1.58959
3	.9202577	.2007701	-0.38	0.703	.6000744	1.411282
head_sex	1.103151	.156296	0.69	0.488	.8356716	1.456245
head_age	.9866477	.0039103	-3.39	0.001	.9790134	.9943416
marital_status	1.237461	.1947037	1.35	0.176	.909081	1.68446
hsize	1.303651	.0345063	10.02	0.000	1.237744	1.373067
working_rate	.7202513	.1184718	-2.00	0.046	.5217623	.9942497
urban	3.772426	.4955351	10.11	0.000	2.916147	4.880139
distance_from_nearest_city_km	1.005677	.0017329	3.29	0.001	1.002286	1.009079
hfi_2016	.9337228	.0123759	-5.17	0.000	.9097789	.958297
_cons	1.904822	.887573	1.38	0.167	.7642364	4.747678

Note: _cons estimates baseline odds.

.
. eststo var9o

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km if outlier==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(12)   = 407.95
                                                        Prob > chi2   = 0.0000
Log likelihood = -1019.2479                             Pseudo R2     = 0.1668
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.6397629	.1677261	-1.70	0.088	.3827015	1.069493
2	.9973537	.2371977	-0.01	0.991	.6257637	1.589601
3	.9198899	.2010763	-0.38	0.702	.599341	1.41188
head_sex	1.103014	.1563433	0.69	0.489	.8354681	1.456236
head_age	.9866498	.0039109	-3.39	0.001	.9790142	.9943449
marital_status	1.237762	.1950188	1.35	0.176	.9089167	1.685584
hsize	1.303639	.0345086	10.02	0.000	1.237728	1.37306
working_rate	.7204561	.1187093	-1.99	0.047	.5216214	.9950838
urban	3.771122	.4973567	10.06	0.000	2.91212	4.883507
distance_from_nearest_city_km	1.005669	.0017506	3.25	0.001	1.002244	1.009107
hfi_2016	.9337354	.0123843	-5.17	0.000	.9097754	.9583264
elevation_km	.9999885	.0003916	-0.03	0.977	.9992212	1.000756
_cons	1.931984	1.295859	0.98	0.326	.5188822	7.193471

```
Note: _cons estimates baseline odds.

.
. eststo var10o
```

Table 10: Column (3)

```
. logistic mpi_status i.protected_status head_sex head_age marital_status hsize working_rate urban distance_from_nearest_city_km hfi_2016 elevation_km slope_o if outlier
> ==0

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(13)   = 408.62
                                                        Prob > chi2   = 0.0000
Log likelihood = -1018.9132                             Pseudo R2     = 0.1670
```

mpi_status	Odds ratio	Std. err.	z	P>|z|	[95% conf.	interval]
protected_status						
1	.645832	.1697918	-1.66	0.096	.3857761	1.081195
2	1.010371	.2411414	0.04	0.966	.6328894	1.612998
3	.9345673	.2053854	-0.31	0.758	.6074997	1.437723
head_sex	1.104407	.1566107	0.70	0.484	.8364198	1.458257
head_age	.9866249	.0039117	-3.40	0.001	.9789878	.9943216
marital_status	1.234538	.1945602	1.34	0.181	.906478	1.681326
hsize	1.30336	.0344837	10.01	0.000	1.237496	1.37273
working_rate	.725377	.1196343	-1.95	0.052	.5250221	1.00219
urban	3.805426	.5037872	10.09	0.000	2.935727	4.932771
distance_from_nearest_city_km	1.005673	.0017498	3.25	0.001	1.002249	1.009108
hfi_2016	.9342036	.0124159	-5.12	0.000	.9101832	.958858
elevation_km	1.000168	.0004494	0.37	0.709	.9992873	1.001049
slope_o	.9633694	.0438053	-0.82	0.412	.8812272	1.053168
_cons	1.638741	1.148166	0.70	0.481	.415074	6.469865

```
Note: _cons estimates baseline odds.

.
. eststo var11o
```

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 10a: Specification test – with outliers

```
. linktest, nolog

Logistic regression                                     Number of obs =  2,856
                                                        LR chi2(2)    = 827.47
                                                        Prob > chi2   = 0.0000
Log likelihood = -1350.9138                             Pseudo R2     = 0.2345
```

mpi_status	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_hat	1.058519	.0528458	20.03	0.000	.9549426	1.162094
_hatsq	-.0574787	.0273531	-2.10	0.036	-.1110898	-.0038676
_cons	.0607132	.0639848	0.95	0.343	-.0646947	.1861211

Appendix 10b: Specification test – without outliers

```
. linktest, nolog

Logistic regression                                     Number of obs =  2,138
                                                        LR chi2(2)    = 412.79
                                                        Prob > chi2   = 0.0000
Log likelihood = -1016.8317                             Pseudo R2     = 0.1687
```

mpi_status	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
_hat	1.151483	.0958212	12.02	0.000	.9636773	1.339289
_hatsq	-.0877156	.0426881	-2.05	0.040	-.1713827	-.0040484
_cons	.0195317	.0759864	0.26	0.797	-.1293989	.1684623

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 11a: Goodness-of-fit test – with outliers

```
. lfit, group(10) table
note: obs collapsed on 10 quantiles of estimated probabilities.

Goodness-of-fit test after logistic model
Variable: mpi_status

  Table collapsed on quantiles of estimated probabilities
```

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.2587	37	44.1	249	241.9	286
2	0.4954	111	109.3	175	176.7	286
3	0.6363	163	162.9	122	122.1	285
4	0.7184	199	194.3	87	91.7	286
5	0.7765	220	213.4	65	71.6	285
6	0.8195	228	228.6	58	57.4	286
7	0.8567	243	239.9	43	46.1	286
8	0.8951	249	249.8	36	35.2	285
9	0.9318	259	261.0	27	25.0	286
10	0.9962	266	271.7	19	13.3	285

```
 Number of observations =  2,856
       Number of groups =     10
Hosmer-Lemeshow chi2(8) =   5.55
            Prob > chi2 = 0.6978
```

Appendix 11b: Goodness-of-fit test – with outliers

```
. lfit, group(10) table
note: obs collapsed on 10 quantiles of estimated probabilities.

Goodness-of-fit test after logistic model
Variable: mpi_status

  Table collapsed on quantiles of estimated probabilities
```

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.4314	65	67.3	149	146.7	214
2	0.5857	113	111.3	101	102.7	214
3	0.6858	132	136.7	82	77.3	214
4	0.7537	156	154.7	58	59.3	214
5	0.8004	179	165.6	34	47.4	213
6	0.8378	174	175.4	40	38.6	214
7	0.8721	180	182.8	34	31.2	214
8	0.9038	190	190.3	24	23.7	214
9	0.9336	194	196.7	20	17.3	214
10	0.9910	201	203.1	12	9.9	213

```
 Number of observations =  2,138
       Number of groups =     10
Hosmer-Lemeshow chi2(8) =   6.81
            Prob > chi2 = 0.5572
```

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 12a: Multicollinearity test – with outliers

```
. vif
```

Variable	VIF	1/VIF
protected_~s		
1	2.28	0.438759
2	3.49	0.286248
3	3.96	0.252809
head_sex	1.47	0.678566
head_age	1.11	0.900649
marital_st~s	1.60	0.623698
hsize	1.19	0.841562
working_rate	1.11	0.898769
urban	1.49	0.671738
distance_f~m	1.40	0.714455
hfi_2016	1.92	0.520099
elevation_km	1.75	0.572865
slope_o	1.75	0.571706
Mean VIF	1.89	

Appendix 12b: Multicollinearity test – without outliers

```
. vif
```

Variable	VIF	1/VIF
protected_~s		
1	2.24	0.445645
2	3.26	0.307020
3	3.75	0.266345
head_sex	1.49	0.669398
head_age	1.12	0.894283
marital_st~s	1.64	0.610045
hsize	1.20	0.836424
working_rate	1.09	0.914961
urban	1.19	0.839517
distance_f~m	1.24	0.803803
hfi_2016	1.38	0.723038
elevation_km	1.42	0.704478
slope_o	1.39	0.716943
Mean VIF	1.73	

Data source: UNPS, WDPA, EWCD, Mu et al. (2022), EEGT

Appendix 13: Robustness to changes in poverty cutoff

```
. tabulate mpi_status_k1 mpi_status_k2, matcell(freq20)

mpi_status |     mpi_status_k2
       _k1 |         0          1 |     Total
-----------+----------------------+----------
         0 |       633        326 |       959 
         1 |         0      2,186 |     2,186 
-----------+----------------------+----------
     Total |       633      2,512 |     3,145 

. local changed = freq20[1,2] + freq20[2,1]

. local N       = _N

. display "Pct changed (k=0.33 vs 0.20): " 100*`changed'/`N'
Pct changed (k=0.33 vs 0.20): 10.36566
```

```
. tabulate mpi_status_k1 mpi_status_k3, matcell(freq40)

mpi_status |     mpi_status_k3
       _k1 |         0          1 |     Total
-----------+----------------------+----------
         0 |       959          0 |       959 
         1 |       312      1,874 |     2,186 
-----------+----------------------+----------
     Total |     1,271      1,874 |     3,145 

. local changed = freq40[1,2] + freq40[2,1]

. local N       = _N

. display "Pct changed (k=0.33 vs 0.40): " 100*`changed'/`N'
Pct changed (k=0.33 vs 0.40): 9.9205087
```

```
. kap mpi_status_k1 mpi_status_k2

             Expected
Agreement   agreement     Kappa   Std. err.         Z      Prob>Z
-----------------------------------------------------------------
  89.63%      61.65%     0.7297     0.0172      42.50      0.0000

. kap mpi_status_k1 mpi_status_k3

             Expected
Agreement   agreement     Kappa   Std. err.         Z      Prob>Z
-----------------------------------------------------------------
  90.08%      53.74%     0.7855     0.0174      45.10      0.0000
```

Data source: UNPS

Appendix 13: Robustness to changes in weights selection

```
. spearman mpi_status_w0 mpi_status_w1 mpi_status_w2 mpi_status_w3, stats(rho)

Number of observations = 3,145

             | mpi_st~0 mpi_s~w1 mpi_s~w2 mpi_s~w3
-------------+------------------------------------
mpi_status~0 |   1.0000
mpi_statu~w1 |   0.8078   1.0000
mpi_statu~w2 |   0.8663   0.6945   1.0000
mpi_statu~w3 |   0.9806   0.8218   0.8864   1.0000

.
```

```
. ktau mpi_status_w0 mpi_status_w1 mpi_status_w2 mpi_status_w3

Number of observations = 3,145

             |   mpi_st~0   mpi_s~w1   mpi_s~w2   mpi_s~w3
-------------+--------------------------------------------
mpi_status~0 |     0.4240
mpi_statu~w1 |     0.3165     0.3620
mpi_statu~w2 |     0.3667     0.2716     0.4225
mpi_statu~w3 |     0.4175     0.3233     0.3767     0.4275
```

Data source: UNPS