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Large-scale monitoring in the DRC's Ituri forest with a locally informed multidimensional well-being index

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ABSTRACT

To monitor quality of life in changing landscapes and assess impacts of interventions, development scholars and practitioners continue to seek sensitive, flexible, practical means of measuring well-being. An approach that has received relatively little attention from development scholars but that is gaining traction among NGOs is the use of a well-being index derived from a list of locally defined and democratically weighted basic necessities. The Wildlife Conservation Society has been piloting a tool called the Basic Necessities Survey (BNS) in and around protected areas in Central Africa and beyond for over a decade. Adapted from consensual relative poverty metrics developed in the UK and Sweden, BNS data can be used to calculate a Well-being Index (WBI) that is locally relevant and comparable. To demonstrate its applicability in a lower-income context, we present findings from the Ituri Region of the Democratic Republic of the Congo (DRC) where over 2,000 households were surveyed using the BNS tool in 2015, 2017, and 2019. WBI scores were lower among traditionally vulnerable and marginalized groups: Indigenous and female-headed households, those with young or elderly heads, and households that were smaller or had high ratios of dependents. WBI varied with livelihood and geography and was sensitive enough to detect group-specific changes over a short time; namely an economic shock concentrated in villages along the main local highway in 2017 when the DRC experienced a major currency devaluation. Scores can be calculated to either incorporate or isolate variability in subjective expectations about what constitutes well-being; we show that expectations differed for Indigenous households and expectations rose faster than assets in this period. Findings build confidence in the utility of this type of locally informed multidimensional well-being metric in low-income regions. Those seeking practical instruments to produce flexible and regionally comparable well-being measures may wish to consider this approach.

1. Introduction

1.1. Measuring and monitoring well-being

Measures of well-being help to identify groups in need, assess interventions, and understand patterns and drivers of variability in quality of life. Many indicators have been developed for this purpose, reflecting different philosophies about what comprises human well-being and different contexts for generating data (Barrington-Leigh & Escande, 2018, Breslow et al., 2016; Corrigan et al., 2018). Broadly, there is increasing agreement that well-being is made up of objective, subjective, and relational components; quality of life is influenced by material conditions, *im*material conditions like human relationships and opportunities, and one's sense of satisfaction with those conditions considering the social context (Boarini et al., 2014). There is less convergence around how these broader concepts can be operationalized in practical measures that recognize well-being's multiple dimensions and facilitate comparative analysis (Loveridge et al., 2020). Researchers and practitioners must choose measures that fit the contexts in which they work. To make these choices, it is helpful

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to have information about how different approaches have performed in different situations, yet available empirical studies are skewed toward a relatively narrow set of indicators and locations (Corrigan et al., 2018, Sollis et al., 2022).

In the field of international development, while there has been significant experimentation with different indices at aggregated country-wide levels (Barrington-Leigh & Escande, 2018), much published household-level research in lower-income contexts is still based on just a few types of indicators, and this is especially true for larger-scale studies. The most commonly used metrics are based on income or consumption, itemizing and monetizing what a household consumes (or earns) in a given time period (Arndt & Tarp, 2017). The World Bank's Living Standards and Measures Survey (LSMS) is an example of one of the biggest initiatives using a consumption-based measure to assess quality of life. The advantage of this type of metric is that it can be meaningfully compared over time and space by making use of price indices and exchange rates.[1] However, practically, it is notoriously difficult to produce a comprehensive inventory of everything consumed by a household, and even more difficult to produce a comprehensive monetized inventory of *income* when there are often myriad income sources, some subsistence, most informal and irregular (Deaton, 2019). Producing legitimate estimates of consumption or income can require substantial training for technicians, and very lengthy surveys can be off-putting for respondents and lead to unreliable information (Fraval et al., 2018). Philosophically, many feel that this type of measure is too narrow to adequately proxy well-being because it lacks relational and subjective dimensions and almost exclusively privileges material conditions, missing elements known to be central to quality of life, like dignity, security, and autonomy (de Haan & Zoomers, 2005; Miller and Hajjar, 2020; White, 2010).

Many approaches have been suggested to incorporate more than just material dimensions of well-being; for example, the Millennium Ecosystem Assessment specifies a framework in which well-being is based on material conditions *and* on four other dimensions of health, social relations, security, and freedom of choice and action (Millennium Ecosystem Assessment, 2005). One challenge in these multidimensional approaches is finding a meaningful way to combine non-monetized dimensions into a single index (Barrington-Leigh & Escande, 2018). Within the past decade, significant progress has been made in developing a family of direct multidimensional poverty measures using weighted indicators from household-level data (Alkire & Santos, 2014). These incorporate multiple dimensions of welfare in a way that is comparable across countries and over time, but do not incorporate subjective aspects of well-being. Incorporating subjective components in an indicator is challenging to do in a way that maintains the useful features of an indicator - something that is practical to measure and is externally legible to facilitate valid analysis and comparison. Questions like "how satisfied are you with your life" can be useful to address subjective aspects of well-being but face limitations comparing across households or over time because they obscure the degree to which objective conditions vs. subjective expectations have changed (Barrington-Leigh & Escande, 2018; Pavot et al., 1991; Pradhan & Ravallion, 2000).

There is also tension between prescribing a kind of universal framework for key components of well-being and leaving room for an index to be informed by local understandings of well-being. There is a long-standing conversation about the extent to which well-being, or conversely, ill-being and poverty, should be individually, locally, or universally defined. Particular concerns include that even when defined at a local level, the needs of marginalized people may not be reflected, and that objective deprivation can be socially normalized (Alkire, 2008; Sen, 1990). Still, there is an increasing emphasis on facilitating meaningful participation of local people in setting the terms of development (Woodhouse et al., 2015), and many argue that well-being should be defined with input from the populations in question, in relation to local contexts and constructs (Loveridge et al. 2020; Sollis et al., 2022). There has been a recent proliferation of well-being research that incorporates local participation, but this has been heavily concentrated in high-income contexts and English-speaking countries and is often focused on defining what well-being means to particular groups rather than attempting to measure and monitor it (Sollis et al., 2022). Because the majority of large-n surveys in lower-income countries have used traditional poverty indicators rather than other framings of well-being, there is relatively little empirical evidence regarding the opportunities and limitations associated with alternative options (Loveridge et al., 2020; Nandy & Pomati, 2015).

One approach for monitoring well-being that strives to incorporate subjective and locally informed perceptions of what is needed for a good life while still producing reproducible and comparable measures is the Basic Necessities Survey (BNS). Designed by Rick Davies for ActionAid Vietnam in 1997 (Davies & Smith, 1998), building on earlier work on consensual measures of poverty in the UK and Sweden (Halleröd, 1994; Mack & Lansley, 1985), the BNS combines indicators of well-being that are locally suggested and easily and reliably observed with a democratic evaluation of which elements are necessary. 'Basic necessities' are "those things that everyone should be able to have, and no one should have to go without" (Davies, 2018). Essentially, a menu of goods, services, and conditions is constructed with local communities and used to calculate a well-being index (WBI) that summarizes how much access a household has to the things that are locally deemed important. The question 'do you think this is a basic necessity' is used to generate collective weightings for the relative importance of each listed item. In contrast to traditional approaches that weight a standard basket of goods by their prices, using locally generated importance weights allows inclusion of items that are recognized as basic necessities but not easily priced (e.g., work that is free from discrimination). Furthermore, by asking whether households have access to certain items and whether they believe they are necessities, it is also possible to separately track changes in assets and changes in expectations, and to test whether subsets of the overall population have systematically different views about what constitutes a basic necessity (Table 1).

The BNS has been gaining traction among conservation and development practitioners because it is relatively straightforward to implement in situations where more exhaustive surveys are not practical. In the early 2000s, the BNS was adopted by the Conservation Measures program of the Wildlife Conservation Society (WCS), one of the world's largest international conservation organizations. WCS's Cambodia team was one of the first to establish a regional monitoring program using the BNS as a tool for measuring changes in quality of life around protected areas (e.g., Clements et al., 2014). In addition to the consensual well-being index, the survey includes questions tailored to a conservation context—information about livelihood activities, use of natural resources, and relationship with protected areas and projects, within the scope of a short survey that can be administered in less than half an hour. In 2014, WCS and partner organizations began extensively using the BNS as an indicator of well-being across the African humid tropics in the USAID-funded Central Africa Regional Program for the Environment (CARPE). Based on lessons-learned over these iterative field campaigns, they have published an

[1] Though see Deaton (2019) for commentary on how this is often less straightforward than assumed.

Table 1
Outcome Variables Examined in this Analysis.

Variable	Measurement and Justification
Well-being Index (fixed)	Sum of goods and services, each item weighted by percent of respondents who said it was necessary in 2015, divided by maximum possible score using those weights. Describes changes in access to goods and services, holding expectations constant.
Well-being Index (floating)	Sum of goods and services, each item weighted by percent of respondents in each different year who said it was necessary, divided by maximum possible score each year. Incorporates changes in access to goods and services *and* changes in expectations.
Well-being Index (group-specific)	For Indigenous households, the sum of goods and services where each item was weighted by percent of *Indigenous* respondents who said it was necessary in 2015, divided by maximum possible score. Accounts for cross-cultural differences in perspectives about what constitutes a basic necessity.
Wealth Index	Sum of goods only, each weighted by quantity owned and initial (2015) price. Weighting material items by their monetary value is comparable to a traditional asset-based poverty index.

open-access protocol summarizing the methodology in detail (Detoeuf et al., 2020).

The BNS and the Well-being Index that it produces represent a useful compromise between sensitivity, generalizability, flexibility, and practicality in landscapes with scant social data. Although scholars and practitioners often have differing agendas and constraints, it can be worthwhile to use common metrics when working in similar contexts (Rasmussen et al., 2017). Understanding the kind of information that BNS surveys can produce will help those considering options for social monitoring. Recently, scholars have called for research on forests and poverty that gives greater attention to under-represented geographies and temporal dynamics (Hajjar et al., 2021). This study presents the results of 5 years of monitoring in the Ituri landscape in the Democratic Republic of Congo (DRC), where the BNS has been used since 2015 to track well-being in households around the Okapi Wildlife Reserve (OWR). We use this landscape as a demonstration case because it is the site with the greatest amount of BNS data collected by WCS thus far, and because it is a site where it is both critical and difficult to monitor well-being. Showing that the approach is useful in the Ituri context builds confidence that it can be feasibly applied in other situations with limited social data.

1.2. Monitoring Well-being in the DRC's Ituri province

The region surrounding the ~14,000 km^2 Okapi Wildlife Reserve in the DRC's Ituri Province is one of the most intact forest landscapes in Central Africa. WCS has been working in the region since the early 1980's. Gazetted as a protected area by the Congolese Government in 1992, and designated a UNESCO World Heritage site in 1996, the reserve contains probably the world's largest population of endangered okapi, and nationally important populations of other IUCN Red-listed species including forest elephants and eastern chimpanzees. The Reserve also protects at least 14 other primate species, 14 ungulate species, almost 400 bird species, many valuable timber species, and some of Africa's densest above-ground carbon stocks (Lewis et al., 2013; Makana et al., 2004; WCS, 2020). For at least 40,000 years, the landscape has been home to the Mbuti and Efe Indigenous Peoples who depend on the forest for much of their daily subsistence (Bailey & Peacock, 1988). They share the landscape with smallholder farmers from various Bantu and Sudanic-speaking ethnic groups. Farmers grow a mix of crops like cassava, peanuts, maize, and beans, in a combination of home gardens and shifting agricultural fields outside the village centers (Brown et al., 2010; Kabuanga et al., 2021). They often also care for small livestock like poultry and a few goats, and source firewood, construction materials, and sometimes foods like wild greens, honey, and bushmeat from the surrounding forest (Terashima, 1998). It is estimated that the forest in and around the OWR provides livelihood opportunities for more than 100,000 people, ~27,000 of whom live inside the reserve (WCS, 2020). Much of the region's population is concentrated in villages located along two unpaved roads that transect the reserve. The Mambasa-Nepoko road (Rte. 4) running from East to West is a national highway and is more traveled and in better condition than the North-South road which forms the eastern OWR border, creating significant geographic variation in access to market centers and infrastructure across the landscape. There is also variation in access to resources within villages. In this region, like elsewhere in rural DRC, social structures are strongly patriarchal and there are long-standing tensions between Bantu/Nilotic majority and Indigenous minority groups; women and Indigenous groups are often subject to discrimination, violence, and marginalization (Ragasa et al. 2012; Van Puijenbroek & Ansoms, 2011). Households are young and childhood mortality rates are high (Kandala et al., 2014).

The Ituri region has experienced significant social and political instability over the past decades, including a civil war in the DRC from 1995 to 2006, with appalling impacts for humans and wildlife (Beyers et al., 2011; Nackoney et al., 2014). Very locally, in June 2012 a group attacked the headquarters of the Reserve, killed six people and all the okapi in a captive breeding program, and destroyed several buildings (UNESCO, 2012). A chaotic period ensued, followed by an increasing presence of the national military, and significant additional funding from USAID in 2015 for investment in security in and around the reserve. During this same period, placer (stream bed) mining of alluvial deposits for gold and diamonds boomed in the region. Partially in response to the gold rush, and partly due to violent conflicts in neighboring regions, there has been a sharp increase of in-migration– with an annual growth rate of 6% in the reserve between 2010 and 2015 (Ntumba et al., 2015). At the national level, economic instability related to mineral prices led the Congolese Franc to depreciate by 72% between 2015 and 2017 (IMF, 2019). In 2018, there was a significant Ebola outbreak in the province (WHO, 2020). To create a more stable environment for conservation, the Wildlife Conservation Society entered a public–private partnership in December 2018 with the Congolese Institute for the Conservation of Nature (ICCN) to co-manage the reserve, with a near-term focus on improving zoning and security (WCS, 2020). Violent attacks have continued in the region around the reserve, with recent attacks by rebel groups against civilians in 2020 and 2022 (UN-OHCHR, 2021; Poulet, 2022).

The social volatility, humanitarian concerns, and high conservation value in the region make the landscape around Ituri's Okapi Wildlife Reserve an important and challenging place for monitoring well-being. In this paper, we demonstrate how the BNS approach has helped to document who is struggling most in this context. We describe how well-being changed in Ituri between 2015 and 2020 to:

1) show how well-being is distributed across the landscape and among different types of households, and
2) highlight places and groups that experienced changes in well-being that were especially acute.

Additionally, we explore different options for calculating the Well-being Index to:

3) show how changes in assets can be tracked separately from changes in expectations, and
4) assess the degree that differences in well-being are due to differences in perspectives about what constitutes a basic necessity.

2. Methods

2.1. Data collection

WCS field technicians collected data from households across an approximately 30,000 km^2 region surrounding the Okapi Wildlife Reserve. The data collection effort involved two phases: 1) focus groups to generate candidates for locally determined basic necessities which were then synthesized into a single regionally specific standard list, and 2) multiple rounds of household surveys throughout the study landscape.

Prior to the main survey campaigns, WCS technicians conducted a series of focus groups centered on the question: "What is something that everyone should have, and no one should have to live without?" These groups were formed with attention to ethnicity, gender, age, and wealth, since all of these can correspond with power dynamics that might discourage input from members in more marginalized positions (Krueger & Casey, 2000; O. Nyumba et al., 2018). Focus groups were held in the villages/towns of Nia-Nia, Epulu, and Mambasa. Although these span the width of the study region, they are all located along the region's main road, and thus the candidate items suggested may be biased toward the types of goods and services most relevant to communities with relatively better access to markets and infrastructure. Within these communities, 11 focus groups were conducted, each including 7–12 members, except for one meeting with 20 Indigenous (Mbuti) women. Specifically, the 11 groups consisted of the following: a) in the village of Epulu: a meeting with Indigenous women, a meeting with Indigenous men, and 4 meetings with Bantu households – one each with women and men, over and under 35 years old; b) in the town of Mambasa: a meeting with fairly wealthy men, a meeting with relatively poor men, a meeting with women of different ages, and a meeting with men under 35, and c) in the town of Nia-Nia: a mixed meeting of women and men.

Candidate items from each group were synthesized into a single list after screening for items that were relevant across the landscape (e.g., not something like "canoe" that would only be applicable for riverfront communities), and that were measurable with clarity (e.g., "a soup pot", rather than "cooking utensils"). The research team selected candidates for the final list such that it contained items ranging from those that almost everyone thought were necessary and almost everyone had, to those that only a few people thought were necessary and very few people had, making sure to include items from each focus group (Detoeuf et al., 2020). Ultimately, the regionally specific list contained 38 items that included 23 material goods (e.g., machete; bicycle; table and chairs) and 15 "services" or conditions (e.g., access to drinking water within a 15 minute walk; women providing healthcare for women). See Appendix 1 for the complete list. The list of goods and services formed the core of the BNS survey instrument, together with questions about household demographics and activities (see Table 2).

Once the list was developed, WCS technicians returned to the villages to apply the BNS. For each listed item, technicians asked respondents whether the household had access to it, how many they had (for goods), and whether that household believed it was indeed a basic necessity. Surveys were designed to take less than half an hour. WCS completed three Basic Necessities Survey campaigns in the Ituri region in 2015, 2017, and 2019. Survey methods were reviewed and approved by the Congolese government and the WCS Institutional Review Board to ensure compliance with Congolese and US federal regulations to protect the rights of human subjects. Surveys were administered on paper in 2015 and digitally with KoboToolbox in 2017 and 2019, in the local languages (Swahili, Lingala, and Kilese) to an adult household member. The field-based team used a two-stage sampling technique in which villages were selected purposefully according to whether they had or would host any WCS projects to enhance livelihood security (e.g., cocoa seedling distribution in previous years, or poten-

Table 2
Covariate Predictor Variables.

Variable	Measurement and Justification
Ethnicity of Head	Simplified into two categories – Indigenous (includes Mbuti and Efe Peoples) and Bantu (includes various Bantu/Sudanic ethnic groups). Ethnicity is a major social determinant in this region (Van Puijenbroek & Ansoms, 2011).
Gender of Head	Households self-defined which member was "head." This tended to be the oldest adult male, but there were a variety of interpretations and configurations. Female-headed households generally indicated single-parent households and are traditionally considered more vulnerable (Freedman, 2011).
Age of Head	A proxy for stage of household life cycle, often associated with livelihood strategies (de Sherbinin et al., 2008). Models include age and age-squared, to accommodate a theoretical non-linear relationship in which households are better off as they mature until heads become elderly (Low, 1986).
Household Size	Based on a definition of "household" as "those who eat around the same fire" (Detoeuf et al., 2020). Household size can proxy labor availability, or demand for resources (Low, 1986).
Dependency Ratio	Calculated as the number of members <15 or >65 years old, divided by household size (following World Bank standards). Dependency ratio serves in conjunction with age of head and household size to describe labor availability.
If household is a New Arrival	Simplified to a binary variable for households arriving after 2010, to separate relatively recent in-migrants from longer-established households since age and arrival year were based on recall and were often imprecise. We chose a threshold of 2010 so that arrival year could not be confused with birth year, as no heads of household were less than 9 years old. Newer immigrants could be more vulnerable if they were refugees from other areas of conflict (Sigler, 2012).
Number of Livelihood Activities	Households could list up to 4 livelihood activities and were asked to include income-generating activities practiced by any household member. We used this as an indicator of livelihood diversification.
Hunting or fishing-based livelihood	Included because of conservation relevance and prevalence in this region (Ichikawa et al., 2017; Wilkie & Carpenter, 1999). This included households that listed hunting, fishing, or bushmeat trade as any of their livelihoods, not just their primary livelihood.
If household mines	Tracked separately because the recent increase in mining is one of the major local drivers of social change and a significant conservation threat (Spira et al., 2019). Mining activities were likely under-reported.
If household has a non-land-based livelihood	A suite of responses (most with frequencies < 5%) were grouped under the category of non-land-based livelihoods. These included business, trades, and various types of professions. We used this simplified indicator to signal participation in income-generating activities that do not depend directly on land or local forest resources.

tial sites for an upcoming sustainable wildlife management program), whether it was safe to go there, and to maximize balance across ethnic groups and livelihood activities. Within selected villages, with the help of the local chief, territories were divided into four quadrants with roughly equal populations. These were used to stratify the selection of a random sample of at least 30 households per village, to capture representative means at the village level, while considering the overall resources required for completing surveys across this geographically extensive landscape (Lakens, 2022). If selected households were not available to be surveyed, neighboring households were invited until the target sample size was reached. In 2017 and 2019, an effort was made to find respondents from previous rounds to build a panel of repeated households tracked over time. When this was not possible, new households were added in 2017 and 2019 to reach the 30-household target for each round in each village. Twenty-four villages were visited in all three rounds, yielding a total of 2,158 household surveys.

2.2. Key variables

The primary outcome variable, Well-being Index (WBI), was generated for each household from the weighted sum of all goods and services to which a household had access, where each item was weighted by the percent of respondents who thought it was a basic necessity. Hence, if 90% of respondents believed a machete was a basic necessity but only 55% believed a bicycle was a basic necessity, machetes impacted a household's WBI score more than bicycles. Goods or services that fewer than 50% of households believed were basic necessities were dropped from the calculation. The sum was normalized by the maximum possible score to create an index between 0 and 1.

The list of goods was also used to generate a Wealth Index. The Wealth Index is more like a traditional asset-based poverty measure and is the sum of only the listed *material* goods that a household has, weighted by the price (converted to USD) and quantity owned. Prices for each good were collected at the village-level at the time that household surveys were administered. Note that expensive and less common goods are weighted more heavily in the wealth index while the most common household goods are weighted more heavily in the WBI, so the wealth index differentiates more within the upper range of households while the WBI score is more sensitive to differences in the lower range. As is common for monetary-based measures, we used a natural log transformation to partially mitigate the strongly right-skewed distribution. When examining changes in the wealth index over time, we used fixed initial price weights so that changes in the wealth index represent changes in what was owned rather than changes in prices of those items.

When comparing WBI scores across different years, we present two forms of the WBI index – one using fixed weights based on initial 2015 responses, and the other using floating weights that incorporate changes in the percent of respondents who said each item was necessary in a given year (Table 1). Similar to a wealth index with fixed price weights, change in fixed-weight WBI isolates changes in access to goods and services, separate from changes in expectations about what is necessary. We present the changes in both measures for the sake of comparison, and then focus on the fixed-weight measure for subsequent analysis of predictors of change. As an additional measure of sensitivity, we calculated a "group-specific" well-being index for Indigenous households using the importance weights derived only from Indigenous households, to explore whether culturally different perspectives about the value of different goods would influence conclusions about relative deprivation in the landscape.

We examined well-being outcomes in relation to a set of household-level covariate predictors describing different demographic and livelihood situations. Table 2 contains a list of the operationalized variables, with notes about how and why they were measured. Most are frequently considered in household-level analyses of conservation impacts on attitudes and well-being in tropical regions (Bragagnolo et al., 2016; Coad et al., 2008). This is certainly not an exhaustive list of factors that influence well-being; the BNS prioritizes a streamlined set of variables to facilitate rapid reliable data collection.[2]

2.3. Data analysis

To assess how well-being changed during the study period, we first conducted bivariate tests for difference in mean well-being indices between survey years. We used unpaired two-sample t-tests with equal variances and checked for robustness with non-parametric tests for equality of medians. Our analysis only considered households within the 24 villages that were surveyed in every round, but to address concern that differences over time could be due to differences in the households sampled within villages each year, we also checked for robustness by examining differences in means for the subset of households that were identified as repeats.[3] We subsequently explored the effect of year in multivariate models predicting household WBI based on household characteristics along with 'village' and 'year' fixed effects, essentially treating village as the panel unit while controlling for household-level characteristics at any given time. We examined the spatial pattern of rising and falling well-being scores across the approximately 30,000 km^2 region surrounding the reserve by calculating and mapping change in WBI for each separate village. We tested for significant differences from 2015 to 2019 and also plotted WBIs for 2017, since comparison of the first and last years can suggest trends but does not detect intervening shocks.

To assess the sensitivity of the Well-being Index to assumptions about the uniformity of local perspectives on the importance of particular goods and services, we present two other descriptive analyses with different approaches for calculating the Well-being Index. We measured how WBI distributions changed when importance weights (the percent of respondents who say each item is a basic necessity) were allowed to vary from survey round to survey round as opposed to using fixed values from the initial baseline survey. We also compared WBI scores for Indigenous People using importance weights derived *only* from Indigenous respondents against scores for Indigenous households when weights were derived from the population of the entire region.

We next used multivariate ordinary least squares (OLS) regression models to examine which household-level demographic and livelihood characteristics were significant predictors of well-being in Ituri. We predicted fixed-weight WBI (Model 1) and log-transformed Wealth Index (Model 2). Models included 'village' and 'year' indicator variables to control for systematic differences across the 24 villages and across the three survey years. We used robust standard errors.

$$\begin{aligned}\text{WBI } \textit{or } \ln(\text{Wealth}) = {} & \beta_0 + \beta_1{}^*\text{Indigenous head} \\ & + \beta_2{}^*\text{female head} + \beta_3{}^*\text{age head} + \beta_4{}^*\text{age head}^2 \\ & + \beta_5{}^*\text{HH size} + \beta_6{}^*\text{dependency ratio} + \beta_7{}^*\text{new arrival} \\ & + \beta_8{}^*\text{num. livelihoods} + \beta_9{}^*\text{hunts} + \beta_{10}{}^*\text{mines} \\ & + \beta_{11}{}^*\text{non-land livelihood} + \beta_{12}\text{-}\beta_{35}{}^*\text{set of village indicators} \\ & + \beta_{36}\text{-}\beta_{37}{}^*\text{survey year}\end{aligned}$$

[2] Ideally, we would have also included a measure of education, but this was mistakenly omitted during one of the survey campaigns.

[3] We used un-paired tests since specific households could not be linked across years with confidence. Although technicians tried to find households surveyed in previous rounds and reliably indicated these as repeats, individual identifiers were inconsistently assigned across years, limiting household-level panel analysis.

To get a sense of the relative importance of village, year, and household variables in explaining variation in WBI, we used a Shapley decomposition to estimate the contribution of each to the model's overall R^2 value (Israeli, 2007). Finally, to explore whether well-being changes were concentrated in particular places or groups (Model 3), we added interactions between survey year and Indigenous heads, female heads, age of head, household size, new arrivals, and, based on results of the mapping analysis, a spatial variable indicating location in a village along the primary East-West road. To accommodate broader spatial variables, we dropped village indicators and incorporated clustered standard errors at the village level.

3. Results

3.1. Households in the Ituri landscape

This analysis draws from 2,158 surveys: 698 in 2015, 717 in 2017, and 743 in 2019.[4] Survey respondents reflected the diversity of social situations in the Ituri landscape. Overall, 14% (n = 303) identified as Indigenous Peoples (Mbuti and Efe). The median age for all household members was 16, and 75% were younger than 35, while the average age of *heads* of household was 45, with a range from 10 to 86. 15% of households reported arriving after 2010 and 6% after 2014. On average, 29% were female-headed, though this number grew during the study period, from 18% in 2015 to 36% in 2019. Average household size was 5.5 (range: 1 to 22).

Agriculture was the dominant activity: overall, 86% of respondents listed agriculture as one of their livelihood activities and 77% listed it as their primary livelihood. The second most common activity was hunting, listed by 23% of respondents. Mining was reported less frequently (6% of respondents). Twenty-eight percent of households reported engaging in a non-land-based livelihood activity of some variety. Non-land-based activities mentioned include artisan, baker, blacksmith, carpenter, electrician, mason, mechanic, painter, tailor, driver, hairdresser, housekeeper, church officer, businessperson, military personnel, nurse, official, police officer, and teacher (with each specific category comprising less than 5% of households). Respondents also gave more general answers like "day-wage worker" and "without activity". Most respondents listed more than one type of livelihood activity, with a median of 2.

3.2. How has well-being changed?

In aggregate, over the whole study period, well-being scores were roughly normally distributed around a mean of 0.46 (range 0.04 to 0.93) for fixed-weight WBI and 0.41 for floating-weight WBI. The wealth index had a highly skewed distribution; 75% of households had wealth indices equivalent to <660 USD but a few households had wealth indices totaling over 30,000 USD.

Indices were not static during the 5-year study period. Average well-being first dropped from 2015 to 2017, then rose again between 2017 and 2019 (Fig. 1). This dip registered whether using fixed or floating weights for the well-being index or using the price-based wealth index (Table 3), so households experienced a decrease in access to material assets. The more complete recovery in fixed WBI compared to the fixed wealth index indicates that services and conditions improved faster than material assets. Changes were similar among the smaller set of households identified as repeats from one round to the next (fixed-weight WBI decreased from 0.47 in 2015 to 0.44 in 2017 but then recovered in 2019; n = 372, $p < 0.05$). Essentially, there is evidence of a regional economic shock concentrated around 2017.

Changes in the well-being index were larger using the version of the indicator that allowed expectations to change from year to year (Fig. 1).[5] The fixed-weight WBI score drops by about 4% from 2015 to 2017, but the floating-weight WBI score drops by 20% (Table 3). This means that at the same time that access to goods and services decreased, expectations about the items 'that every household should have and no household should have to do without' rose.

3.3. Where has well-being changed?

Of the 24 villages that were surveyed every round, an equal number showed significant ($p < 0.05$) positive (n = 7) vs. negative (n = 7) changes in average WBI scores. The remaining 10 villages showed no significant change between 2015 and 2019, though several experienced perturbations in 2017 (Fig. 2). There is spatial clustering among villages with positive trends, with hotspots around the intersection of the region's two primary roads and in the northeastern part of the landscape. Those around the more central juncture tended to start with higher WBIs and those in the more remote northeastern region started with lower WBIs, but both clusters generally increased. Villages with significant declines were more spatially dispersed and tended to have mid-range initial WBI scores (except Epulu, reserve headquarters, where initial WBIs were quite high).

3.4. How does well-being vary across households?

Well-being scores varied *within* villages and years based on characteristics of individual households. In general, households had lower well-being scores when household heads were Indigenous or female (Table 4). Lower scores were associated with higher ratios of dependents, but controlling for dependency ratio, larger households were better off. Well-being scores were lower for households with younger heads, then increased with the age of heads of household, then slowed and decreased for elderly household heads. Holding other variables constant, whether a household head arrived in the region within the past 10 years did not predict well-being scores (this was also true in a robustness check among households arriving after 2014). Generally, higher well-being scores were associated with households reporting greater numbers of livelihood activities, although those who reported hunting or mining tended to be worse off and those with non-land-based livelihoods tended to be better off.

Predictors of the Well-being and Wealth Index were generally consistent, though WBI was more sensitive to the stage of the household life cycle (age of household head) (Models 1 and 2, Table 4). 'Year' remained statistically significant when controlling for household- and village-level factors, continuing to register a shock in 2017 in both well-being and wealth indices (Models 1 and 2, Table 4). A Shapely decomposition of the model predicting fixed-weight WBI scores (Model 1) indicated that the set of measured household-level variables accounted for about half of the explained variation in well-being scores (49%). The village that households belonged to accounted for another 49%, and the survey year accounted for just 2% of explained variation in scores during this relatively narrow time range. In the model predicting wealth index (Model 2), 'village' accounted for 37% and 'year' accounted for 6% of explained variation. Much of the variability in our quality-of-life indicators remains unexplained, i.e., many other fac-

[4] In 2017, 434 households were identified as repeats from the 2015 round, and in 2019 this decreased to 372.

[5] The items that comprised the index were held constant in all survey years, but the weights for each item changed based on the percent of households in a given year who said it was a basic necessity.

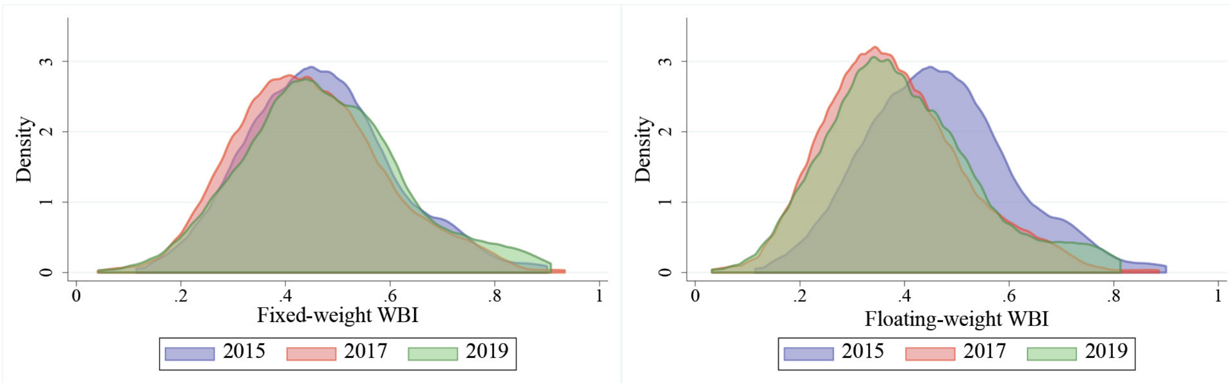

Fig. 1. Density estimates of well-being scores as they change over the study period. At left, we used fixed weights from 2015, based on the percent of households who believed each item was a basic necessity. At right, respondent expectations about what constitutes a basic necessity were allowed to change from year to year. Rising expectations exaggerate decreases in well-being.

Table 3
Summary Statistics and Bivariate Tests for Change Over Time in Well-being Indices.

	2015	2017	2019	Change 2015 to 2017	Change 2015 to 2019
Fixed-weight WBI	0.47	0.45	0.47	−0.02**	0.01
Floating-weight WBI	0.47	0.38	0.40	−0.09***	−0.07***
Wealth Index	6.0	5.6	5.9	−0.4***	−0.1†
Number of Households	698	717	743		

†p < 0.10, *: p < 0.05, **: p < 0.01, ***: p < 0.001 based on two-sample tests for equal means.
Wealth Index values are natural-logarithmic transformed.

tors also influence the goods and services that households can access.

Some of the biggest differences in well-being scores were due to ethnicity. The difference between Indigenous and non-Indigenous households persisted but decreased when we used the importance weights specific to Indigenous respondents to calculate WBI scores for Indigenous households (Fig. 3). Using the fixed-weight WBI measure, average WBI for everyone was 0.46, compared to an average of 0.35 for Indigenous households. Using Indigenous weights, the average Indigenous household WBI increased to 0.42 (but overall WBI increased to 0.51 when Indigenous weights were applied to everyone; Indigenous households were less likely to think many items in the list were basic necessities).

3.5. Which households experienced well-being changes most acutely?

The average temporal effect showed a drop in 2017 of about 0.027 points, or about 6% of average 2015 WBI, followed by recovery in 2019. However, some households experienced much larger effects because the shock was concentrated in specific areas and among particular types of households. A model that allowed well-being to vary differently among specific groups (Model 3, Table 4) indicated that the shock in 2017 was experienced most strongly along the main E-W road (where initial WBI scores were generally higher). Female-headed households were especially hard hit, while Indigenous-headed households were less affected than others, though they remained consistently well below the average WBI for non-Indigenous households (Fig. 4). The same is true for households with higher ratios of dependents to adults – they had lower well-being indices in general but were less impacted by the 2017 shock.[6]

[6] Group-specific effects were robust to controlling for village.

4. Discussion

4.1. Detecting differences in Well-being in Ituri

In the Ituri landscape around the Okapi Wildlife Reserve, variation in the Well-being Index echoes patterns evident in many studies using traditional poverty and human development indices. The generally lower well-being scores among Indigenous, female-headed, natural-resource dependent, and young or elderly households align with those who tend to be economically marginalized in many low-income regions (Angelsen & Wunder, 2003; Biyase & Zwane, 2018; Cho & Kim, 2017; Jayne et al., 2003; Mutabazi et al., 2015). Our proxy for recent immigrants was the only predictor measured that showed no significant association with WBI, possibly because immigration occurred under a range of circumstances – from wealthier families moving to the market centers from less stable regions to poorer young men participating in the gold rush. Like other recent studies, we found that those who reported mining-based livelihoods had relatively lower well-being (Sovacool, 2019). Hunting and fishing-based livelihoods were also associated with lower well-being scores, aligning with the well-established finding that poorer households are often most dependent on forest resources (Angelsen & Wunder, 2003; Coomes et al., 2004). Complementarily, households with higher well-being scores were more likely to be engaged in non-land-based activities, in line with an established trend where off-farm jobs are associated with wealthier households (Barrett et al., 2001). Households with more kinds of income generating activities tended to be better off in this landscape, corresponding with the theory that a diversity of income sources can lead to better resilience in the face of volatility (Bryceson, 1999). Villages with better road access had generally higher scores while more remote areas had lower scores, a pattern typical in rural areas across the tropics (Bird et al., 2011). Generally, the fact that many predicted patterns about household well-

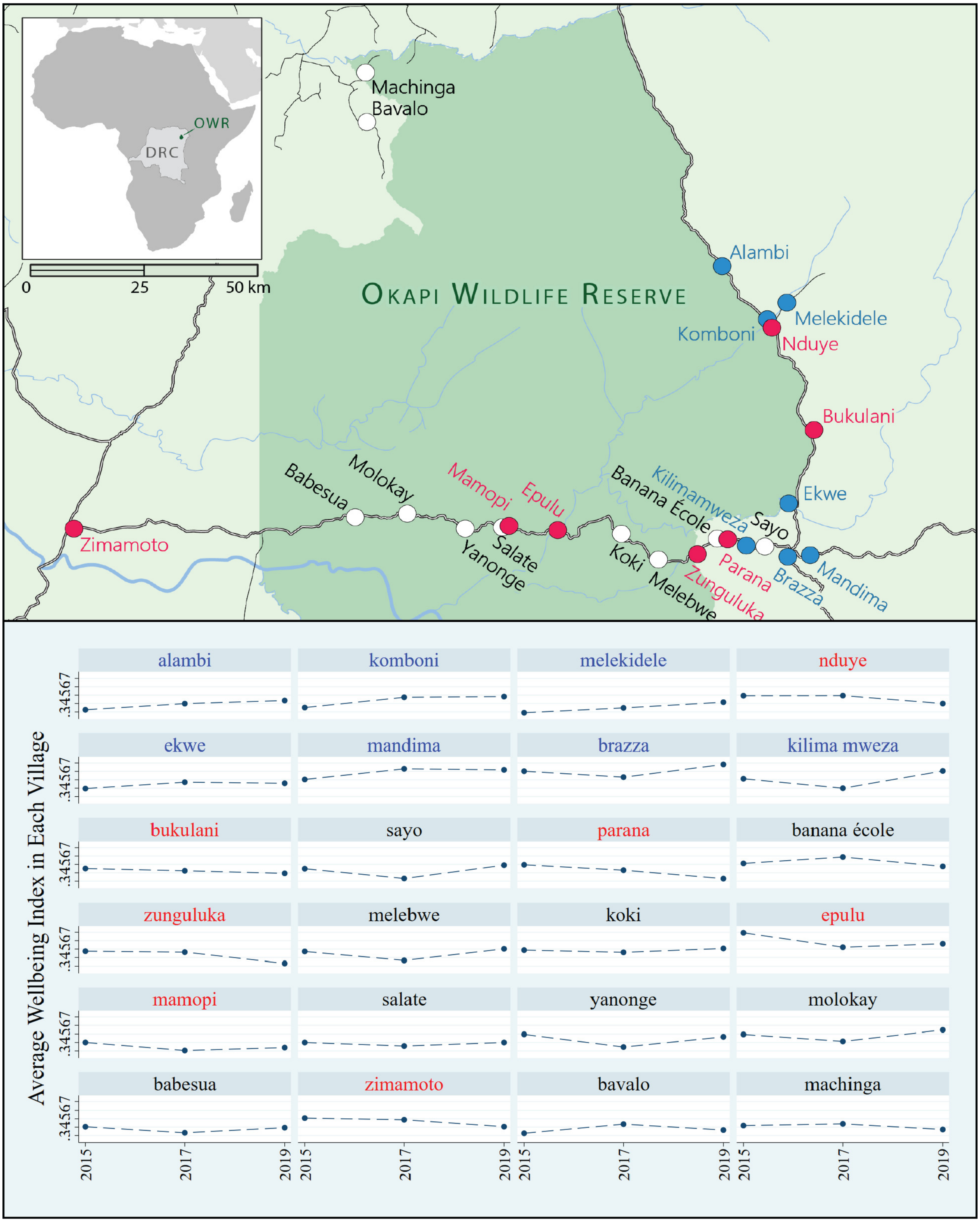

Fig. 2. Village-level change in Well-being Index across three survey rounds. Blue indicates villages with significant increases from 2015 to 2019, red indicates significant decreases, and black text or white dots correspond to no significant change. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

being registered in the BNS data builds confidence that WBI can serve as a meaningful indicator.

In addition to cross-sectional variation between households, the BNS proved able to illuminate people and places experiencing changes in well-being. During the short span of 5 years between 2015 and 2020, well-being increased in some villages and decreased in others, with an average landscape signal indicating a dip in 2017 followed by a partial recovery. Among the many

Table 4
OLS Models of Well-being as a function of Household Characteristics, Village, and Time.

	Model 1 WBI	Model 2 Wealth	Model 3 WBI
Household Characteristics			
HH is Indigenous	−0.10 ***	−0.72 ***	−0.09 ***
HH is Female	−0.04 ***	−0.28 ***	−0.03 *
Age of HH	0.003 **	0.07	0.002 *
Squared Age of HH	−0.00003 **	−0.00004	−0.00002 *
Household Size	0.01 ***	0.10 ***	0.01 ***
Dependency Ratio	−0.02 *	−0.24 *	−0.07 ***
HH Arrived After 2010	0.002	−0.02	−0.01
Num. of Livelihood Activities	0.03 ***	0.20 ***	0.03 ***
Hunting or Fishing Livelihood	−0.03 ***	−0.36 ***	−0.05 ***
Mining Livelihood	−0.04 ***	−0.45 ***	−0.07 **
Any Non-land-based Livelihood	0.03 ***	0.32 ***	0.03 **
Village-level Controls			
Includes Village-level Controls	Yes	Yes	No
Along Main E-W Road			0.10 ***
Survey Year (Baseline is 2015)			
2017	−0.03 ***	−0.49 ***	0.01
2019	0.002	−0.17 **	0.01
Group-specific Time Trends			
HH is Indig. × 2017			0.02 †
HH is Indig. × 2019			−0.001
HH is Female × 2017			−0.04 *
HH is Female × 2019			0.01
HH Age × 2017			0.0001
HH Age × 2019			0.0002
Household Size × 2017			−0.005 †
Household Size × 2019			−0.004
Dependency Ratio × 2017			0.07 **
Dependency Ratio × 2019			0.02
Recent Arrival × 2017			0.02
Recent Arrival × 2019			−0.01
Along Main Road × 2017			−0.08 *
Along Main Road × 2019			−0.01
Constant	0.28 ***	5.12 ***	0.28 ***
Num. Obs.	2,095	2,080	2,095
R^2	0.43	0.36	0.31

†: $p < 0.10$, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.
The table presents results of models using fixed-weight WBI scores. Floating-weight WBI scores generate a very similar pattern in terms of significance and direction of relationships, with the exception that 2019 scores remain significantly depressed relative to the 2015 baseline.

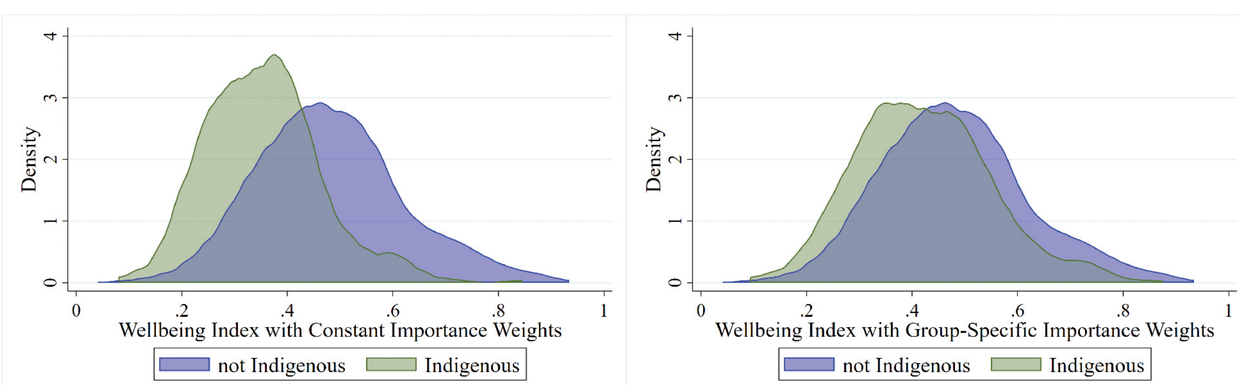

Fig. 3. Distribution of well-being scores for Indigenous and non-Indigenous households. Left: Landscape-level importance weights were used for both groups of households. Right: Scores for Indigenous households were calculated with weights specific to Indigenous respondents.

sources of volatility in the region, the one most convincingly associated with this signal of a widely experienced economic shock during this period is the severe devaluation of the Congolese Franc that occurred at the end of 2016 (XE.com Inc., 2021). The drop in our 2017 indices represents an actual loss of access to assets, not just a change in their value since the wealth index was calculated with fixed price weights. The finding that the shock was felt most acutely in villages along the main road is consistent with the currency devaluation explanation because these households were more integrated into the national and cash-based economy. Conversely, Indigenous households that tended to be less integrated into the cash-based economy were less impacted; they were also poorest at the outset and had less far to fall. We see a similar story for households with high dependency ratios. Female-headed households may have experienced the shock more intensely because they were less able to turn toward forest-based activities like hunting and fishing due to customary gender roles, and several key informants indicated that this was not a safe period for women

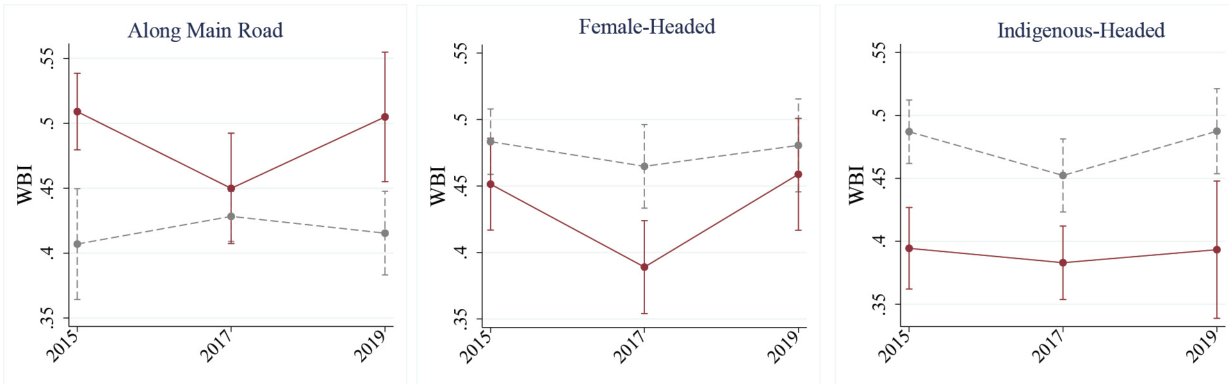

Fig. 4. Linear predictions of WBI as it changes over the study period for respondents in different groups, with 95% confidence intervals. Solid lines show modeled predictions for the indicated group, and dashed lines represent the comparison group of everyone else.

to travel alone to forests or agricultural fields, thus their livelihood safety-net options were limited.

Apart from the signal of a broadly experienced dip in well-being in 2017, there were also idiosyncratic trends in WBI across the region. Some changes had very locally-specific explanations – like the high but declining indices in Epulu village where OWR is headquartered. The 2012 rebel attack on OWR offices led to a substantial loss of employment, and many current employees now keep households in Mambasa or other locations, shunting incomes to other villages. Local informants suggested that changes in several locations were related to the initiation or abandonment of nearby mining areas, many of which are ephemeral and relatively clandestine. Villages with generally improving WBIs were concentrated around the larger town of Mambasa, a hub located at the intersection of the region's two roads, and in a more remote cluster near a major Catholic mission near the village of Nduye. Interpreting locally specific patterns over just a few points in time calls for caution and triangulation, but monitoring trends in a spatially explicit way can highlight potential drivers of change in well-being that merit further study. During the study period, WCS's efforts were focused on preparing for the shift to a public–private partnership to co-manage the reserve, and collecting baseline social data to support an impending investment by the EU Sustainable Wildlife Management Program - there were no major new livelihood projects introduced at this time. Ongoing monitoring will allow protected area managers to more confidently distinguish shocks from normal variability and help establish a robust baseline against which to measure effects of future interventions.

4.2. Challenges, limitations, and next steps in Ituri

Many of the limitations associated with the data from these initial rounds in Ituri are not related to the approach to measuring well-being per se but rather to challenges in sampling and disclosure that are common among rapid social surveys. Collecting household survey data in large campaigns can create a sense of swooping in, extracting information, and leaving communities wondering how they benefit from sharing their information (Datta, 2018). A long-term presence in and commitment to the region helps to mitigate this. For the case we describe, the surveys were done in the context of a multi-decade relationship between WCS and the communities around the Okapi Wildlife Reserve. WCS employs local staff, and Congolese field technicians carry out the surveys and present results back to the communities. Nonetheless, there are indications that activities like mining and charcoal production are under-reported (these are illegal inside the reserve) and/or there is selection bias such that some types of households were less likely to be captured (e.g., miners and recent arrivals) (Matthysen, 2018; Sylvia et al., 2020). Those present and willing to be surveyed when the technicians visit a village may be a more established subset of the community. Adding a temporal dimension creates additional challenges. Some of the changes in household demographic characteristics from one round to the next, like the proportion of female-headed households, may be partially attributed to bias in the households available to be surveyed in ongoing rounds of data collection if female-headed households were more likely to remain present in the village and be willing to be surveyed. This is ameliorated in our models predicting well-being indices by controlling for demographic characteristics, but it weakens our ability to make conclusions about changes in the predictor variables themselves.

On a related note, much has been written about the drawbacks and benefits of using households as a unit of analysis (e.g. Deaton, 2019) – household members do not all have equal access to resources, characteristics of a traditional "household head" only partially capture potentially relevant aspects of the household, and it is not always clear which member qualifies as the head. Our use of a 'household-head' approach limits what we are able to learn about the way gender impacts well-being, since answers about whether a "household" has access to a list item like "women participate meaningfully in village decisions" likely depend on the gender of the respondent, and the way resources are shared within households can be especially disproportionate in cultures with very patriarchal gender norms (Rodríguez, 2016). Tracking change over time multiplies complications with a household unit of analysis tied to the characteristics of a household head because household composition can change. Furthermore, intra-regional migration and multi-sited households are common. Consequently, household level panel data can be difficult to obtain and tricky to interpret, even when repeat households are identified. Bias can arise when households that are most "stable" and likely to be found in repeated rounds of monitoring are not necessarily most indicative of regional demographics. Our approach of controlling for household characteristics in repeated samples from the same villages addresses these issues partially but imperfectly. We do not capture the well-being of households that leave the communities, which can be an important story in areas with instability and conflict. Future research assessing the potential of monitoring with a well-being index tied to individuals rather than to households would be useful.

The importance of attending to change over time in often rapidly evolving social contexts has long been emphasized by human-environment scholars working in sub-Saharan Africa (Guyer et al., 2007). We demonstrate that the BNS and WBI can be a practical tool for large-scale descriptive monitoring. However, in the short survey, we do not capture all or even most of the factors that potentially influence household well-being. Model R^2 values indicate that less than half of the variation in household well-being scores is explained by variables in our study. While this is typical for studies of social outcomes which are seldom reducible to simple and tidy mechanistic relationships, it is important to keep in mind that the correlates identified here are neither deterministically nor even necessarily causally related to well-being. Those considering adopting this type of measure can add questions to the survey instrument to capture other important elements believed to influence well-being within particular contexts.

As they have gained confidence in the WBI metric, WCS intends to use it for impact evaluation, in addition to monitoring for social changes and identifying areas of concern in landscapes where they work. For analyses that aim to identify causal relationships and measure project effects, choosing a metric for measuring well-being is an initial step; other steps include developing a theory of change that connects an intervention or phenomenon to potential effects on well-being, and implementing a study design that supports comparisons against a plausible counterfactual (Woodhouse et al., 2015). These other steps remain challenges regardless of the metric chosen, and often require sampling strategies that are tailored to individual projects and questions. The fact that we detected short-term changes and group-specific impacts of a shock build confidence that WBI can be sensitive enough for program evaluation. However, it is possible that even with project-specific sampling designs, changes associated with a particular project may not be captured by the index or may impact it in a delayed way. There are more targeted tools to capture short-term changes and pathways of change associated with specific interventions (for example, the Most Significant Changes technique (Davies & Dart, 2005)), but researchers, managers, and donors should also be interested in broader measures to understand the extent that specific project impacts translate into effects on well-being more generally, how long these effects persist, and how they fit into the context of other influences on well-being. Our findings of significant spatial and temporal variation in well-being scores are a reminder that these "background" patterns must be taken into account when planning and evaluating projects, and that conservation activities may be dwarfed by other forces affecting local well-being.

4.3. Defining and measuring well-being

Our results from Ituri thus far speak to the question of whether metrics like the WBI are useful alternatives to more traditional consumption-based metrics. The defining feature of the Well-being Index and earlier related consensual poverty metrics is the list of component goods and services that is both produced and weighted according to local perspectives, rather than externally imposed prescriptions for the types of things that people should need. In comparison to indices based on inventories of household consumption weighted by price, WBI easily incorporates elements that are difficult to value monetarily, allowing for a wider conception of necessities and well-being. There has been criticism of approaches that define well-being in terms of meeting only basic needs (e.g., Gasper, 2007), yet "something every household should have, and no one should have to live without" is potentially a more solid benchmark than "something a household may want". That said, if there was interest in resolving a different portion of the well-being spectrum, it would be possible to apply the same methodology with an altered prompt, e.g., "what are things that households have access to when they are doing well," and rely on the democratic importance weightings to emphasize the most consistently appreciated items.

Deciding which items should comprise the final landscape-level list is probably the most ambiguous and important part of the process. Decisions about the final list should be made thoughtfully by the research team rather than mechanistically tallying the number of times something is mentioned in a focus group. Moving from menus of candidate items generated across several groups to a single list of ~35 specific but broadly relevant items that capture locally important dimensions as well as variability in well-being requires optimizing over many considerations (see Loveridge et al., 2020 for recent progress on this front). Additionally, analysts using the WBI for impact evaluation must check that the index is not masking components that are endogenous to the project being assessed, e.g., assessing the well-being impacts of a project that distributes cookstoves, while using a cookstove as one of the basic necessities that makes up the index. Once the core list is formed, the survey is straightforward to apply, and a short list of yes-or-no questions about common goods and services can be answered with relatively little of the measurement error associated with recall bias and survey fatigue common in more extensive survey instruments (Fraval et al., 2018). Using a standard list of goods and services across the entire landscape makes it easy to compare well-being scores within the region, but comparisons against regions using other lists are less straightforward. The index measures (roughly) the proportion of the things that people locally think are necessary that a given household has. When comparing within landscapes using the same list, the comparison is valid in absolute terms, but when comparing indices from different lists, the comparison is valid only in relative terms. This could be partially addressed by turning to the subset of list components that generate the complimentary wealth index and using price indices to determine whether assets in different regional lists have very different monetary values. WCS is also experimenting with a "core" list of 10 items that are included in the landscape-specific lists for all of their sites in Central Africa (derived from 40 focus groups across multiple sites in Congo and DRC), so that inter-landscape comparisons could be made directly with this subset of items (these items are starred in Appendix 1).

If different groups within the same landscape have very different views about what constitutes a basic necessity, this undermines the validity of a democratic consensual definition of well-being (Fahmy et al., 2015). That said, we show that data produced from the standard list can be flexibly analyzed after collection, relaxing assumptions about the degree to which local preferences are uniform. While it is true that scores in Ituri were sensitive to both the list of goods and the set of people included in assessing their importance, it is helpful that we can examine *how* sensitive. A few studies of consensual metrics in South Africa and Vietnam have found high correlations (0.90 and above) in their rankings of basic necessity items across characteristics like gender, race, age, and urban vs. rural respondents (Davies, 2007; Wright et al., 2010), though they point out that in places with less market influence, there may be greater variation. In our case, Indigenous households had distinctly lower weightings for most items on the list, clearly signaling cultural differences in what constitutes a basic necessity, as has been documented in other contexts (e.g., Kant et al., 2014). Indigenous households ranked well below the majority of the population regardless of the weighting scheme, but the difference between the groups narrowed when using importance weights that were specific to each subpopulation. Indigenous households had fewer of the BNS items but did not feel proportionally worse off because they were less inclined to believe that those items were important. Note, though, that if the things that mainly Indigenous households believe are basic necessities are not adequately represented in the landscape level list, their scores could also be biased in the other direction. The danger that well-being will be indexed according to the views of the local majority is tempered by the potential to use the same data to assess whether subpopulations have dramatically different views about the necessity of particular items, and to calculate different indices to reflect this. In our analysis, we used fixed weights to focus on comparing the material situations of different groups, but we show that it is possible to calculate and compare distances between what people have and what people think is important, even when what counts as important varies.

When there is temporal variation in what items are viewed as important, we can incorporate or isolate people's changing expectations over time. In this case, whether indices were weighted by 2015 expectations, current expectations in a given year, or prices of goods, the cross-sectional patterns of variation between households were fairly similar. This is reassuring as it means that the ability to identify struggling groups is relatively robust to analytical choices – female-headed and Indigenous households were worse off on average, regardless of which version of index we used. Triangulation across different index formulations can also be instructive when there *are* differences. For example, the age of household head is not a significant predictor of the wealth index, where more expensive assets are weighted more heavily and there is more variance when young households purchase things like motorcycles. Comparing fixed and floating-weight WBIs allows us to see that expectations are rising faster than assets, which can create the perception of increased impoverishment even when access to goods and services are improving. Rising expectations could be particularly significant in communities with repeated visits and surveys by NGOs, and this is important to keep in mind when using well-being measures that incorporate subjective components in impact evaluation.

5. Conclusion

The Well-being Index is a useful alternative to metrics based on inventories of income or consumption because of the flexibility in what it can include, and because it is relatively straightforward to collect the information needed to generate an externally interpretable measure that is sensitive to underlying variation. Although the measure does not perfectly capture the nuances of what comprises human well-being, the WBI avoids externally imposed definitions of well-being that can be culturally or contextually inappropriate by drawing on local focus groups to generate a standard list that allows comparison between households and across time. The information produced with the BNS can track changes in expectations separately from changes in access to goods and services, addressing concerns that subjective measures can mask objective deprivation, and allowing analysis of variability both in what people have and what people want. As implemented in Ituri thus far, the BNS has proven to be an instrument that can provide a sensitive and robust measure of well-being and highlight groups that are struggling in a key region for conservation and development. WCS has begun to use the Basic Necessities Survey and its well-being index extensively in Central Africa, Madagascar, and Cambodia and has recently adopted it as a standard social indicator for their programs worldwide. Other organizations like Bird Life International, World Wildlife Fund, and the Jane Goodall Institute have also begun using the Basic Necessities Survey in their work. By sharing results and lessons from these efforts thus far, scholars and practitioners can collaboratively build on these experiences to create strong social monitoring programs that reflect local assessments of needs and well-being.

CRediT authorship contribution statement

Jessica L'Roe: Methodology, Formal analysis, Visualization, Funding acquisition, Writing – original draft, Writing – review & editing. **Diane Detoeuf:** Methodology, Supervision, Data curation, Writing – review & editing. **Michelle Wieland:** Project administration, Funding acquisition, Writing – review & editing. **Bernard Ikati:** Investigation. **Moïse Enduyi Kimuha:** Investigation. **François Sandrin:** Investigation. **Odette Angauko Sukari:** Investigation. **Junior Nzale Nkumu:** Investigation. **Heidi E. Kretser:** Writing – review & editing. **David Wilkie:** Conceptualization, Funding acquisition.

Data availability

The data that has been used is confidential.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A – List of Goods and Services

Access to electricity
Access to veterinary products
Access to adult learning *
A bed and mattress
A bicycle
A car
Improved woodstoves/cookstoves or fuel-efficient stoves *
Access to drinking water within a 15-minute walk *
A 1-hectare field
A freezer
A house in sheet metal
A hunting net
Improved seeds
A 20-liter jerry can
A machete
Meals twice a day*
Micro-credit
Money for family healthcare
Money for school
A motorcycle
Access to natural resources within an hour's walk from home *
A pan
A phone
A plate
Live chickens or poultry *
Access to animal protein 3 times a week *
Quality healthcare
A radio
A sewing machine
Small livestock
A tractor
A transform unit within 1 km
A TV
A WC
Women medics available to care for women in health clinics *
Women participate in decision-making in the village *
A wooden table and chairs
Making a living without discrimination: same salary for the same work *

(*)Starred items are from WCS's core list used across all Central African landscapes

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