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Spatially heterogeneous effects of collective action on environmental dependence in Namibia's Zambezi region

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ABSTRACT

Many poor rural households depend on products from non-cultivated environments for subsistence and commercialization. Collective action schemes, such as community-based natural resource management (CBNRM), aim at maintaining natural resource quality and thus potentially contribute to the sustainability of environmental income sources. Little is known about whether and under which contextual conditions these schemes effectively promote environmental income generation or imply trade-offs between wildlife conservation and socioeconomic development. We rely on a unique combination of original farm-household data with a rich set of spatiotemporal covariates to quantify environmental income and dependency in Namibia's Zambezi region at the heart of the Kavango-Zambezi Transfrontier Conservation Area. We then estimate the effect of CBNRM on environmental income and dependency in a quasi-experimental regression-based approach. Controlling for historical variables that affected selection into formal CBNRM schemes, we further explore the role of contextual variation in exposure to tourism activity. Results suggest that CBNRM fosters livelihood strategies that are, on average, more dependent on the environment. However, this effect is driven by outcomes of households that live in close proximity to touristic enterprises, where such livelihood strategies align better with other income generating opportunities than in areas where agriculture represents the only viable economic alternative.

1. Introduction

The development of poor rural areas often critically depends on the access to and availability of products from non-cultivated environments for both subsistence and commercial uses. Lange et al. (2018) estimate that the environment directly contributes on average 14 percent[1] to household income across the full rural–urban continuum in a large sample of low-income countries. Rural households in the humid and dry forest zones of low and middle-income countries were found to generate roughly 25 % of their total income from environmental sources (Angelsen et al., 2014).

Nevertheless, the relationship of rural household (HH) wealth and the environment is characterized by complex synergies and trade-offs (Lee & Barrett, 2001). Environmental income not only reduces rural poverty, it also serves as a safety net (Wunder et al., 2014), and favorably affects income equality (Vedeld et al., 2007; Nguyen et al., 2015), because poor rural HHs consume more environmental products than wealthier ones (Angelsen & Dokken, 2015). On the other hand, options to substitute for environmental products are often limited, leading to overuse in many populated rural areas throughout the developing world (Barbier, 2010). This can result in the degradation of natural resources, for example, when landless and therefore asset-poor HHs face labor market constraints and thus cannot substitute environmental income through formal employment. Hence, when environmental income contributes a substantial share to total HH income, natural resource degradation can stifle rural development and aggravate poverty (Cavendish, 2000).

The design of sustainable poverty alleviation and rural development strategies also hinges on closing the research gap with respect to contextual determinants of such poverty-environment linkages. We address this research gap by studying how

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[1] Own calculations based on Lange et al. (2018) comprising timber and non-timber forest products and protected area net-present values, excluding cropland, pastureland and subsoil assets.

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community-based natural resource management (CBNRM) affects environmental income and dependency at household level. A review of other known determinants of environmental income and dependency is provided in S1 and motivates the covariate selection in our empirical strategy.

Our study area is Namibia's Zambezi region (see Fig. 1), which is located at the center of the world's second largest Transfrontier Conservation Area (Kavango Zambezi – KAZA TFCA). Natural resources are of vital importance to rural livelihoods in this region, which is characterized by variation in potentially relevant spatial determinants of HH environmental income and dependency (Kamwi et al., 2015). Namibia is also the birthplace of community conservancies, a common form of CBNRM, which aims at harmonizing wildlife conservation and socio-economic development (Republic Of Namibia, 2016). Wildlife tourism is considered one of the key pathways to achieve such harmonization as it can provide complementary, including environmental, income to local communities (Naidoo et al., 2016) and thus enhance local support for biodiversity conservation (Naidoo et al., 2011). But, high wildlife densities may also increase the risk of human wildlife conflict and related costs to local communities (Khumalo & Yung, 2015; Nattrass, 2021b). Such potential tradeoffs between nature conservation and socio-economic development have been repeatedly discussed in the academic literature in and beyond our study area (Suich, 2010; Stoldt et al., 2020). In this literature, the role of CBNRM and environmental income as cause and mechanism behind potential poverty-environment trade-offs has not yet been studied using counterfactual-based empirical methods.

Namibia represent a natural laboratory to address this research gap. A total of 86 community conservancies have been established throughout the country since 1996 and 16 are spread across the Zambezi region (MEFT/NACSO, 2021). This makes our study area well-suited for analyzing human environment interactions. We exploit spatial variation in exposure to alternative income opportunities, including tourism, and find that CBNRM in the Zambezi region has promoted environmentally benign livelihood strategies, but occasionally also failed to do so. Our empirical approach benefits from enriching an original set of household survey data (collected in collaboration with local partners during 2019) with spatiotemporal variables and including historical selection determinants dating back to the early 1990s.

The paper is structured as follows: We first provide a theoretical background on environmental income and dependency, including the related academic debate on human-environment relationships and the factors that moderate this relationship in rural areas (Section 2). We then document the empirical approach and data used to explore our theoretical expectations (Sections 3 and 4). Results and their policy implications are displayed and critically discussed thereafter (Sections 5 and 6).

2. Rural livelihoods and environmental income

The environment provides natural resources, which we conceptualize as natural capital (Sjaastad et al., 2005) with stock-dependent income flows. The stock of natural resources provides HHs with environmental products and ecosystem services. Environmental products are rival goods for consumption or commercialization depending on whether HHs are subsistence or market-oriented. The overuse of environmental resource in many populated rural areas of the developing world is a result of limited options to substitute for environmental products (Barbier, 2010).

Environmental products are generally non-cultivated and serve as fuel, food, fiber or fodder (Vedeld et al., 2007). In the study area, these include e.g. (fire)wood, medicinal plants such as devils claw (*Harpagophytum*), and fish. Many of these products are mainly used for subsistence and have thus been called *hidden harvest* due to their absence on local and global markets (Campbell & Luckert, 2002). This aspect makes quantification of environmental income inherently more challenging. Additionally, there is a multitude of concepts that uses forest and environment as well as income and dependence to describe economic human-nature relations (Angelsen et al., 2012; Das, 2010; Mamo et al., 2007; Nerfa et al., 2020; Vedeld et al., 2007; Wunder et al., 2014). Scholars use several terms interchangeably and inconsistently, such as forest income, forest dependency, environmental income, environmental dependency and forest environmental income. Henceforth we use environmental income to refer to the absolute income from environmental product consumption or commercialization and rely on the share of environmental in total income as a measure of environmental dependence.

2.1. Understanding spatial variation in environmental income and dependence

Conceptually, environmental income is jointly determined by the supply of and the demand for environmental products. Environmental supply side determinants include important factors of production (López, 1994), for example, soil quality and renewable but exhaustible stock resources including freshwater and plant or animal populations to be harvested and hunted (Perman, 2011). Resource pollution, i.e. the depletion of quality and quantity through environmental degradation by both environmental and anthropogenic factors causes disturbances in the supply of environmental products and services (Haberl et al., 2007). The case of devil' claw harvest in southern Africa and Namibia explicitly showcases this development (Stewart & Cole, 2005).

Natural resource access and endowments thus become important supply side determinants of rural HH's environmental income. For example, depending on natural resource availability, HHs tend to rely more on environmental products when land for agricultural production becomes scarce (Angelsen et al., 2012). Soil quality on the other hand was shown to exhibit a positive effect on total HH income, but mainly through agriculture as an income channel (Bravo-Ureta et al., 2006). Which income channel dominates, however, may be co-determined by demand side factors, such as access to agricultural markets and business opportunities in conservation. This conjecture partially motivates our heterogeneous treatment effect analysis in section 5.4.

Using proxies of natural resource availability, recent studies by Watmough et al. (2019) and Yeh et al. (2020) show that remote sensing data can considerably improve predictions of general rural wealth indicators. Watmough et al. (2019) also show that the amount of bare agricultural land surrounding a HH is associated with the poorest HHs. Pritchard et al. (2019), however, find no correlation between environmental income or dependency and HH's woody resource availability, which they measure at the village level. Different measurement levels and data generation processes may lead to seemingly contradicting findings especially in global studies.

Demand side factors equally affect the choice, consumption, and commercialization quantities of environmental products by households. Asset and income-poor rural HHs, for example, rely more on environmental resources for their income than the relatively better off (Angelsen et al., 2014; Cavendish, 2000). Correspondingly, Finan et al. (2005) and Deininger et al. (2009) find that poverty decreases with an increase in land endowment. Other HH characteristics, such as family size, age, gender, and education levels were shown to be important predictors of environmental income, but their role varies across study sites (Angelsen et al. 2014; Cavendish 2000; Kamanga et al. 2009; Vedeld et al. 2007).

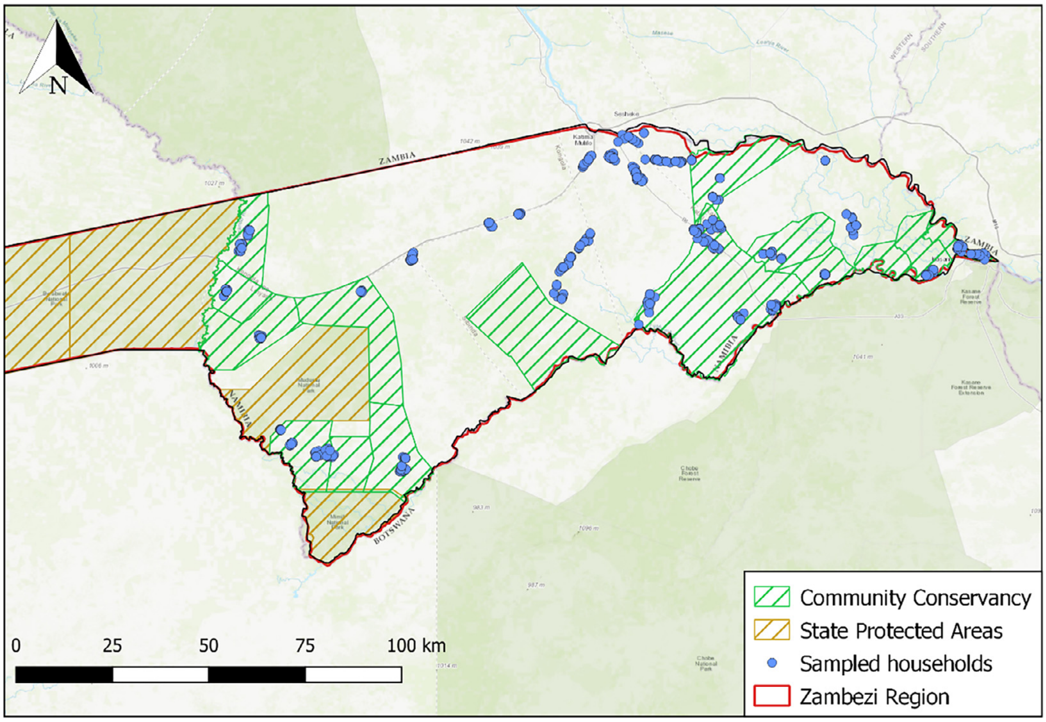

Fig. 1. Zambezi Region, Namibia. Source: own illustration.

Income shocks are another known potential determinant of environmental income and dependency (Wunder et al., 2014). Temporal increases in demand for environmental products, for example, can be the result of shock coping strategies adopted by poor households (Angelsen & Dokken, 2018). But, even though environmental products can help the poor in times of need, overreliance may result in a poverty trap caused by a vicious circle of environmental degradation (Barbier, 2010).

Besides HH specific characteristics and exogenous shocks, local context factors modulate environmental dependency. This is evident for market access and integration, which can promote the specialization towards commercially attractive livelihood strategies (Nielsen et al., 2013). For example, HHs with a high degree of integration in labor markets tend to be less dependent on environmental products, because HHs can generate higher off-farm income from formal employment and businesses as shown by Belcher et al. (2015).

Meanwhile, conservation can also provide market opportunities, such as in wildlife tourism, to which some CBNRM schemes are exposed (Yergeau, 2020). This important industry in African economies encompasses consumptive and non-consumptive tourism ventures (Naidoo et al., 2016). But, income opportunities in wildlife tourism may not spatially coincide with access to agricultural and labor markets, because wildlife presence is subject to different spatial dynamics (Brennan et al., 2020).

In Namibia's Zambezi region, our study area, direct income from employment in tourism plays a minor role (Kalvelage et al., 2020b). But, rural HHscan still benefit from tourism activity via indirect channels such as informal service provision and commercialization opportunities or redistribution of fees from consumptive tourism. Since Namibia's approach to CBNRM aims chiefly at wildlife conservation, a potential trade-off may arise if conservation measures effectively increase wildlife densities, in particular, along the various wildlife corridors crossing the Zambezi region (Nattrass, 2021b; Suich, 2010). Human-wildlife conflict may then compromise rural development and, consequently, societal support for conservation.

Hence, we hypothesize that HH's livelihood choices in our study area will adjust to spatial variation in the supply of and the demand for natural resources, which includes heterogeneous exposure to income opportunities in the tourism sector. These choices would appear to be an important mechanism behind regionally heterogeneous levels of environmental dependence and corresponding woodland cover conservation (Meyer et al. 2021).

2.2. Determinants and outcomes of collective action

Self-organized collective action to overcome the commons dilemma can improve the provision of environmental products and services when rural communities formulate and effectively enforce rules for natural resource access and use (Bodin, 2017; Ostrom, 2010). This has led some governments to condition the partial devolution of use and management rights to local communities on established CBNRM criteria (Measham & Lumbasi, 2013; Dressler et al., 2010), especially in southern Africa (Whande et al., 2003). Formal CBNRM rules may sometimes replace informal traditional land rights systems, which are often based on agriculture, especially in Namibia (Bollig & Vehrs, 2021). Motivation to apply for CBNRM status, i.e. implementing transfers of land use rights, may thus vary across local economic contexts. In Namibia, Silva & Mosimane (2014) identified both economic and social motivations as drivers of participation in CBNRM. Nature conservation objectives may therefore drive collective action only when they synergistically align with both economic interests and social motivations at private and community-level. Such heterogeneity in motivations to engage in state-promoted CBNRM may then mask the effect of genuinely collective resource management on local livelihood strategies. Findings from existing empirical studies of average effects seem to confirm this conjecture. For example, Angelsen et al. (2014) and Bandyopadhyay et al. (2010) find a positive effect of membership in forest user groups and conservancies on *total* household income, but no measurable effect on environmental dependency.

We thus further hypothesize that more secure property rights support environmental income generating activities that align with wildlife conservation goals in tourism zones, but expect to find agriculture-based livelihood strategies (including extensive cattle grazing systems) to rather conflict with environmental income sourcing strategies in zones without tourism activity. The mosaic landscape of CBNRM initiatives in the Zambezi region allows us to test this and the hypothesis formulated in section 2.1 above using a rich data set of household characteristics and income determinants.

3. Study area and data sources

The Zambezi Region in north-eastern Namibia, consists mainly of Zambezian Baikiaea woodlands and to a lesser extent of the North East rivers ecosystem zone that includes floodplains (Mendelsohn et al., 1997). The region covers 14,785 km^2 and is surrounded by the rivers Zambezi in the north east, the Chobe in the South East, the Linyanti in the South and the Kwando in the South West, which form natural borders to Zambia, Zimbabwe and Botswana. The region borders Angola in the North. The Zambezi Region is embedded in the KAZA TFCA, the world's second largest TFCA, with numerous national parks and wildlife migration corridors cutting through the region (Naidoo et al., 2018). Community conservancies, Namibia's formalized CBNRM schemes, have become an integral part of wildlife management throughout the Zambezi region, covering over 50 % of state-owned land and hosting 225,000 people (http://www.nacso.org.na/). Wildlife is actively managed and commodified by trophy hunting and safari tourism, respectively (Mbaiwa, 2013), where hunting has generated substantial controversy, potentially undermining conservation efforts (Nattrass, 2021a). Yet, both wildlife populations and socio-economic development were found to be positively affected by conservancy establishment on average (Meyer et al., 2021; Bandyopadhyay et al., 2004).

The Zambezi region has a population of 98.849 (2016) with over 70 % of the residents living in rural areas (Namibia Statistics Agency, 2017). In national comparison, the region has relatively suitable natural conditions for agriculture (Mendelsohn, 2006). Although the majority of the rural population in Zambezi depends on crop production and cattle herding, there is little intensification of agricultural activities and some linkages to domestic or regional value chains (Hulke et al., 2020). Katima Mulilo is the only urban center in the region and functions as an economic hub for cross-border trade and logistics, food procurement and processing, governmental control and other basic infrastructure, e.g. in health and education (Zeller, 2009). In the region, 39 % of the population lives below the poverty headcount rate, compared to 27 % in the whole country (Republic Of Namibia, 2016). Unemployment rates are high with almost 37 % of the working population and half of the population aged between 15 and 34 being unemployed (Namibia Statistics Agency, 2019).

We use original HH data from a cross-sectional survey conducted between April and September 2019. Our dataset covers 652 HHs in the rural part of Namibia's Zambezi Region. The questionnaire uses a 12-month recall period and covers key HH-level determinants of total and environmental income. We followed a two-stage stratified random sampling procedure with HHs clustered in official enumeration areas (EA). First, EAs were stratified into c*onservation* (conservancies & national parks)*, intensification* (agriculture & infrastructure) and *other* zones*.* Data on EAs was obtained from the Namibian Statistical Agency (NSA). Second, HH listings identified all HHs in each EA, which were then randomly drawn from. Due to missing data that followed no specific pattern, 19 HHs were excluded, leaving 633 HHs from the analysis.

Euclidean distances of HHs to key infrastructure and environmental sourcing locations in km are calculated using Open Street Map data. Nightlight radiation change data is derived from National Centers for Environmental Information of National Aeronautics and Space Administration at 30 arc seconds (aprox.1 km) grid resolution and measured in W/m^{-2}. Soil organic carbon is provided by the International Soil Reference and Information Centre which is publically available from the *African soil atlas* (Hengl et al., 2015) at 250 m grid resolution and measured in g/kg. Both covariates are derived using a point value at the HH location. Biomass change from 2008 to 2018 in tones is extracted from a biomass change map (see S6), which we generate following Wingate et al. (2016) using ground truth data of Kindermann et al. (2021) at 300 m grid resolution. The resulting summary statistics for all 633 HHs are presented in Table 1 and data sources in S2.

4. Empirical strategy

We quantify environmental income from products that are *wild* and *uncultivated* and harvested from natural areas including forests following the principles of the Poverty Environment Network, but using a 12 month recall period (Angelsen et al., 2014). Values of environmental products are calculated based on local market prices. Indirect values, such as erosion control and flood prevention as well as non-use values such as cultural and existence values are not included. Environmental income is thus defined according to Sjaastad et al. (2005):

> "[...] natural rent realized, through consumption or alienation, within the first link of a market chain provides a precise and logically consistent measure of environmental income under conditions of perfect competition." (Sjaastad et al., 2005).

4.1. Identification of CBNRM impacts

CBNRM outcomes are potentially biased due to self-selection of HHs into these schemes. Quasi-experimental empirical approaches, such as covariate matching can help to address selection issues, but remain subject to unobservable bias (Ferraro & Miranda, 2014). Covariate matching finds a group of HHs that are not conservancy members (the control group) but which are very similar in observable characteristics to conservancy members (the treated group). This enables a comparison of outcomes among very similar treated and control HHs, assuming a reduction in self-selection (Rosenbaum & Rubin, 1985). The statutory selection process to establish a conservancy in the study area is not regulated by universal and easily observable criteria that one could control for (Republic Of Namibia, 2016). This also holds for HH conservancy membership. We consider HH conservancy membership as the treatment and rely on propensity score weighted regressions, estimating the propensity score as follows:

$$T_i^C = \alpha + \beta X_i + \delta S_{it} + \varepsilon_i \quad (1)$$

where T_i^C indicates community conservancy membership of the HH i as treatment. X_i are socio-economic and demographic characteristics of HH i. S_{it} are either pre-treatment observations, i.e. multiple periods of historical spatial covariates characterizing the local context of each HH before community conservancy membership or spatial contextual covariates, such as distance to rivers or national parks. ε_i is an idiosyncratic error term, independent and identically distributed, with mean zero and constant variance. Local context

Table 1
Outcome and covariate data summary statistics.

Group		Variables	Mean	sd	Median	Min	Max
Income	1	Environmental gross income per head	137.58	656.60	0.00	0.00	13,750
	2	Environmental income share	0.13	0.28	0.00	0.00	1.00
Household characteristics	3	HH head male	0.52	0.50	1.00	0.00	1.00
	4	HH head age	51.55	17.59	49.00	20.00	91.00
	5	HH head education [years]	5.41	3.15	6.00	0.00	15.00
	6	HH head inmigration	0.71	0.45	1.00	0.00	1.00
	7	Mafwe Ethnicity [dummy]	0.22	0.42	0.00	0.00	1.00
	8	Subia Ethnicity [dummy]	0.39	0.49	0.00	0.00	1.00
	9	Dependency ratio	40.79	23.75	42.86	0.00	100.00
	10	Asset index	3.00	1.42	3.00	1.00	5.00
	11	Agricultural land [ha]	9.56	18.77	4.94	0.00	300.00
	12	TLU	5.05	11.98	0.34	0.00	122.80
	13	Labor shock [dummy]	0.60	0.71	0.00	0.00	3.00
	14	Wildlife conflict crop damage [dummy]	0.14	0.34	0.00	0.00	1.00
	15	Wildlife conflict livestock damage [dummy]	0.08	0.27	0.00	0.00	1.00
	16	Wildlife conflict property damage [dummy]	0.02	0.14	0.00	0.00	1.00
Collective action	17	Conservancy member [dummy]	0.38	0.49	0.00	0.00	1.00
	18	Social Network index	25.67	24.57	19.48	0.00	100.00
	19	Trust index	2.99	1.42	3.00	1.00	5.00
Market Integration	20	Travel distance [h]	0.25	0.15	0.25	0.02	0.71
	21	Distance to B8 & C49 [km]	8.46	13.90	2.77	0.00	59.04
	22	Distance to rivers [km]	38.99	39.00	20.40	1.00	151.48
	23	Distance to wildlife corridor [km]	10.64	12.79	4.72	0.00	37.93
Spatial	24	Nightlight radiation change [W/m^{-2}(–|-)]	0.82	1.96	0.00	0.00	14.00
	25	SOC [g/kg]	9.92	3.36	9.00	4.00	23.00
	26	Sand content [g/kg]	721.60	68.66	731.00	387.00	833.00
	27	Biomass change 2008 – 2018 [t/ha]	–2.67	8.40	–3.47	–46.40	47.74

Source: own illustration.

variables are defined either as point values at the HH location or in terms of aggregate values in a buffer around that location. Buffer width should correspond to the average scale of interaction of HHs with their environment (Avelino et al., 2016). According to Mosimane et al. (2014), who identified interactions scales of HHs with their environment for the KAZA TFCA, this implies an approx. 1.5 km radius.

We choose HH characteristics (X_i) that may have affected HH decisions to become conservancy members, but should have remained independent of conservancy outcomes, such as gender, age, education, and ethnicity. Pre-treatment covariates (S_{it}) include nightlight radiation, three pre-treatment periods of woodland cover, sand content, travel distance to the region's capital, and distances to national parks, highway, schools and rivers. Descriptive statistics of covariates are documented in Table 1 and pre-weighting statistics of treated (conservancy) and non-treated HHs are contained in S9.

To estimate treatment effects we use the covariate balancing propensity score (CBPS) following Imai & Ratkovic (2014). The estimated propensity scores from Eq. (1) are used subsequently as weights in Eq. (2) and (3). This accounts for pre-existing systematic differences, i.e. the selection bias, between members and non-members of conservancies and preserves all observations (Olmos & Govindasamy, 2015). Additionally, the covariate balancing propensity score simultaneously optimizes treatment assignment and covariate balance, and increasing robustness against misspecification (Imai & Ratkovic, 2014). This is achieved via weighting the control group HHs such that their weighted covariate distribution matches with that of the treatment group. This places greater emphasis on covariates with strong predictive power (see Imai & Ratkovic (2014) p. 245 – 247 for details).

4.2. Model specification

To estimate environmental income and dependency, we proceed in two steps. First, we estimate a double hurdle and a fractional logit model in a baseline regression to explore associations between predictors of environmental income and dependence, respectively. Second, we re-estimate these models with covariate balancing propensity score weights from Eq. (1) to account for observed selection determinants.

Environmental income is zero for part of the population (see S5), leading to a zero-truncated dependent variable. Following Humphrey (2013), we consider these to be genuine zeros, i.e. HHs making rational and utility maximizing decisions that are optimal with regard to the allocation of time for generating income from the environment und known opportunity costs. This motivates a hurdle model approach, because zeros constitute a corner solution to the underlying constrained utility maximization problem. Generating income from the environment is also influenced by an *a priori* decision to engage in collection of environmental goods. The two decisions are therefore chronologically sequential, suggesting the use of a "full double hurdle model" (Jones, 1992) or "double hurdle dependent model" (Garcia Villar & Labeaga, 1996; Humphrey, 2013). This model is estimated as follows:

$$Y^*_{1i} = \alpha_1 + \beta_1 X_{1i} + \delta_1 S_{1i} + \varepsilon_{i1} \quad (2)$$

$$Y^*_{2i} = \alpha_2 + \beta_2 X_{2i} + \delta_2 S_{2i} + \varepsilon_{i2} \quad (3)$$

$Y_{2i} = Y^*_{2i}$ if $Y^*_{1i} > 0$
$Y_{2i} = 0$ if $Y^*_{1i} \leq 0$

where Y^*_{1i} is a latent variable capturing unobserved utility from deciding to collect environmental goods, Y^*_{2i} represents observed utility (i.e. income that is log transformed where 0 is kept at 0) from consumption and commercialization of environmental goods, generating income of HH *i*. X are all socio-economic and demographic characteristics of HH *i*, S are spatial characteristics of the HH *i* in pre-survey years, and ε_{i1} and ε_{i2} indicate the idiosyncratic error terms ($iid(0, \sigma^2)$). The model includes the inverse Mills ratio in the second (outcome) part of the estimation equation as it assumes $corr(\varepsilon_{i1}, \varepsilon_{i2}) \neq 0$ (Heckman, 1979) and is estimated using the *heckit* command contained in the *sampleSelection* package in R (Toomet & Henningsen, 2008).

For the case of environmental dependency, Y is measured as a share, i.e. continuous but bounded between 0 and 1 (see S5). We therefore estimate a fractional logit model (Papke & Wooldridge, 1996) using Eq. (2) and the same covariates as in Eq. (2) and (3).

We use (i) sampling weights in the propensity score estimation stage (Eq.1) and (ii) sampling weights multiplied by covariate balancing propensity score weights (see section 3.1) in the outcome models (hurdle and fractional logit, except in the baseline specification) as suggested by Ridgeway et al. (2015). We present these findings in Sections 5.3. Except for the baseline specification, we exclude trust and social network indicators from estimating the hurdle and fractional logit model and instead explore the effect of collective action on social network factors and trust as potential intermediate outcome indicators (see S15).

4.3. Covariate selection

All covariates are described in Table 1 and motivated in section 2. As a supply side proxy for natural resource availability, we use the change in vegetation biomass between 2010 and 2018. To control for demand side determinants, we include HH head gender as male (dummy), age (in years) and education (in years), ethnicity (either Mafwe or Subia, as they are the main ethnicities), dependency ratio, and migration history. We use the first principal component derived from a list of standard household durables to control for asset endowment. Agricultural land (in ha) and tropical livestock units (TLU) enter the estimation as separate predictors reflecting key productive assets. We also control for shocks to the HH labor force and human-wildlife conflicts in terms of crop, livestock, and property damage, which are known to affect income and livelihood choices. Conservancy HHs may be more prone to human wildlife conflict, which could confound the effect of conservancy membership. We avoid this by controlling for human wildlife conflict explicitly.

HH participation in collective action for conservation is represented by a conservancy membership dummy. We approximate social network capital using the sum of information on who (quality) and how often (quantity) HH members have contact with (Zhang et al., 2017) and trust as the first principal component of reported levels of trust in various dimensions, such as in formal and informal leadership.

Output and labor market integration of the HH is represented via travel distance to the region's capital, Katima Mulilo (Schielein et al., 2020) as well as distances to the *trans-caprivi highway* (B8) and the C49 highway. Euclidian distances to the nearest river and to wildlife corridors serve as proxies for income opportunities from wildlife and tourism. Nightlight radiation change from 2004 to 2013 approximates local socio-economic development and agro-ecological suitability is measured in terms of soil organic carbon.

4.4. Heterogeneous treatment effect analysis

As indicated in section 2, prior work suggested heterogeneous conservation outcomes from CBNRM in the region. Meyer et al. (2021) showed that conservation outcomes of collective action spatially coincide with exposure to tourism opportunities in the study area. To test our hypothesis that this is linked to environmental income and corresponding livelihood choices (section 3.2), we estimate the hurdle and fractional logit model for two subsets. These subsets are defined by their distance to tourism areas, represented by tourism accommodation such as lodges and campsites using Open Street Map Data. We subset our dataset into areas below and above median Euclidean distance to these tourism areas. We use the median due to its robustness against outliers. Additionally, we control for social networks and trust in these two subsets (see S16).

All models are checked for multicollinearity and we exclude variables with a variance inflation factor above five. Using a Breusch-Pagan test, we test for heteroscedasticity and address this issue through calculating heteroscedasticity-consistent coefficients, if applicable. The tobit model is estimated as heteroscedastic tobit regression model using *crch* (Messner et al., 2016).

5. Results

Gross environmental income results are reported in S4, with an average environmental gross income per HH member of 137.58 N$ and standard deviation (SD) of 656.60 N$. This corresponds to 13 % of total gross income per capita, which constitutes our environmental dependency outcome with a SD of 28 %. Both outcomes exhibit substantial spread and therefore varying importance of environmental income for HHs. Main products collected by HHs in the Zambezi region are building materials such as wood, thatching grass, reeds, poles and clay but also firewood, fruit and medicinal plants (see S3).

5.1. Baseline results

We start by exploring the baseline results of estimating double hurdle and fractional logit models without covariate balancing propensity score weighting in columns 2, 3 and 4 of Table 2, respectively.

Results from column 2 and 3 can be interpreted as semi-elasticities, i.e. a *relative* change in selection probability and quantity of environmental income from an *absolute* change of one unit in the explanatory variables. Results from column 4 show a percentage change in dependency given an absolute change of one unit in the explanatory variables. Collective action, represented by conservancy membership, is in line with our hypothesis and associated with 21 % higher environmental product collection and 52 % higher amounts of products. Membership is also associated with a 17 % increases in environmental dependency, indicating relevant associations of membership on all outcomes. Trust increases the probability of HHs to collect products from the environment by 9 % and quantity collected by 16 %. Effect sizes of social networks on all outcomes are small. An increase in nightlight exposure at the HH location of one $W/m^{-2}(-|-)$ is associated with a decrease of 6 % in environmental product collection quantity, suggesting socio-economic development, which is often associated with reduced reliance on the environment. Soil organic carbon exhibits a small but negative association with environmental income and dependency, suggesting agricultural income opportunities. Biomass change has a small positive effect on environmental income but no effect on dependency. Various other confounding variables are correlated with environmental income and dependency (see S10).

5.2. Spatial determinants of collective action

Results from estimating Eq. (1) are depicted in Table 3 and identify HH-level and spatial determinants of collective action, i.e. HH conservancy membership.

In the covariate balancing propensity score regression (column 2), two periods of pre-treatment woodland cover before conservancy establishment are the most important determinants of conservancy membership. Covariate balancing propensity score also optimizes balance in other important pre-treatment characteristics, such as ethnicity (as either Mafwe or Subia) of the HH head, nightlight exposure, and travel distance. Fig. 2 compares covariate

Table 2
Effects of collective action and spatial determinants of environmental income and dependency.

	Income		Dependency
	Selection	Quantity	
Intercept	−0.060 (0.404)	−0.128 (1.374)	0.119 (1.183)
Collective action & social capital			
Conservancy member	0.207 (0.122)$^{\cdot}$	0.518 (0.217)*	0.166 (0.247)
Social Networks	0.006 (0.002)**	0.008 (0.006)	−0.003 (0.004)
Trust	0.091 (0.037)*	0.162 (0.092)$^{\cdot}$	0.028 (0.070)
Spatial determinants			
SOC	−0.004 (0.018)	−0.008 (0.015)	−0.031 (0.038)
Nightlight change	0.012 (0.031)	−0.063 (0.029)*	−0.010 (0.079)
Biomass change | 1500 m Buffer	0.004 (0.007)	0.010 (0.007)	−0.000 (0.012)
Other Controls			
HH Characteristics	Yes		
Shock & wildlife conflict	Yes		
Distances	Yes		
invMillsRatio	2.664 (1.539)$^{\cdot}$		
logLik	−405.299		−195.619
Num. obs.	633	309	633
R^2		0.848	
Adj. R^2		0.834	
RMSE		0.768	

Note: Estimations based on unweighted data set.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.
Robust SE clustered at village level for fractional logit are provided.

Table 3
Household and spatial determinants of HH conservancy membership.

	Covariate Balancing Propensity Score	Probit GLM
Intercept	0.082 (0.584)	0.071 (0.908)
Male	0.188 (0.118)	0.083 (0.120)
Age	0.009 (0.157)	0.006 (0.004)$^{\cdot}$
Education [years]	−0.017 (0.176)	−0.020 (0.020)
Mafwe	−0.427 (0.182)*	−0.102 (0.159)
Subia	−0.322 (0.194)$^{\cdot}$	−0.037 (0.138)
Nightlight 1998	0.226 (0.242)	0.107 (0.048)*
Woodland cover 1984	−2.705 (0.175)***	−1.767 (0.319)***
Woodland cover 1989	−0.141 (0.193)	0.163 (0.342)
Woodland cover 1994	1.038 (0.187)***	0.462 (0.215)*
Sand content	0.002 (0.125)	0.001 (0.001)
Travel distance	0.250 (0.260)	−0.206 (0.591)
Distance to National Park	−0.024 (0.173)	−0.016 (0.004)***
Distance to highway	0.012 (0.149)	0.006 (0.006)
Distance to school	−0.003 (0.170)	−0.004 (0.001)**
Distance to river	−0.009 (0.200)	−0.006 (0.002)*
AIC	730.88	674.81
BIC	743.70	746.02
Log Likelihood	−320.96	−321.40
Deviance	641.90	697.98
J-statistic	0.0043	
Num. obs.	633	

Source: own illustration.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.

balance across alternative balancing approaches in terms of standardized differences in means.

5.3. Influences of collective action on environmental income and dependency

The covariate balancing propensity score approach clearly leads to the best covariate balance (see Fig. 2) and overlap of the propensity score (see S8). We thus use the covariate balancing propensity score score to weigh each observation according to its estimated probability of being a conservancy member (see S13) and then re-estimate equation (2) to (4). Results are shown in Table 4 and indicate the effect of conservancy membership on the choice of selecting environmental income as livelihood source (column 2), environmental income quantity (column 3) and environmental dependency (column 4) using covariate balancing propensity score propensity score weights (See S11 for full results).

Among conservancy members, more HHs select the environment as a livelihood strategy and extract on average higher values of environmental products compared to non-conservancy members. Assuming unconfoundedness after matching, collective action in community conservancies thus on average promotes livelihood strategies that rely on the environmental. Estimates using GLM probit model weights suggest that findings are robust (see S14, column 5–7).

5.4. Heterogeneous treatment effects

As stated in section 3.4, we expect heterogeneous treatment effects moderated by tourism opportunities, which favor more environmentally reliant livelihood strategies. As a proxy for expo-

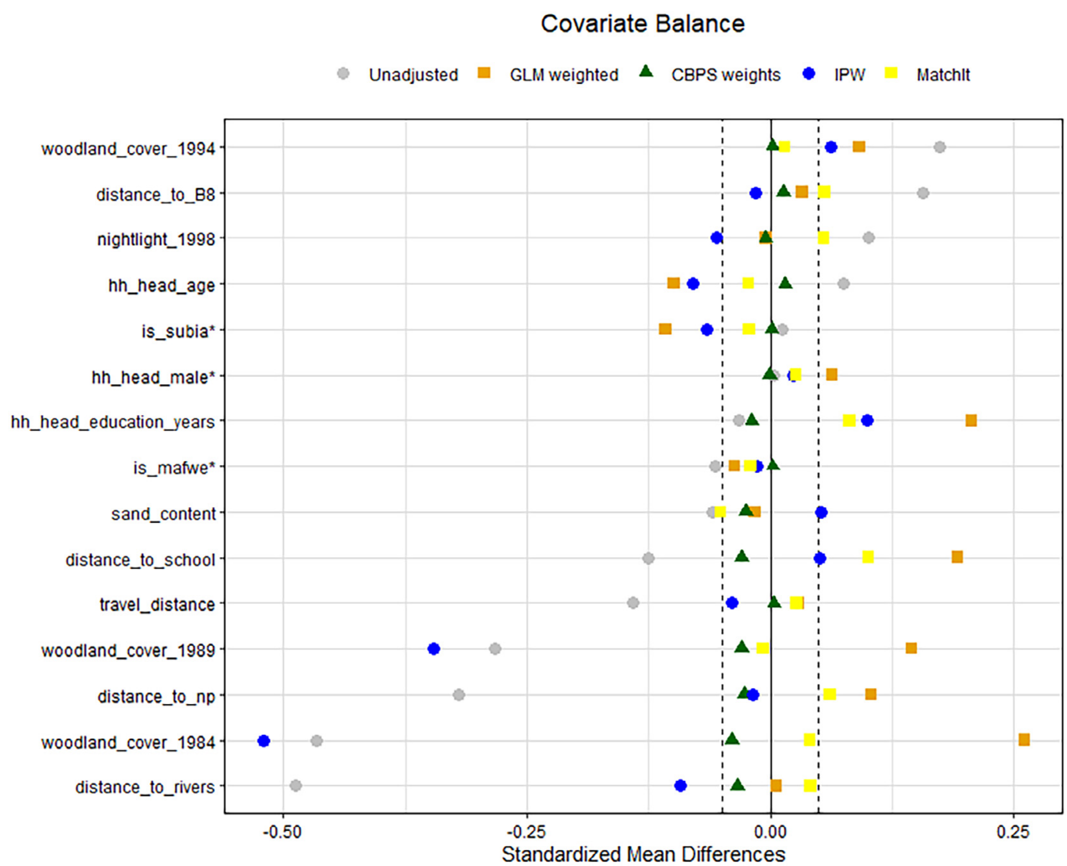

Fig. 2. Covariate balance using different matching setups. Source: own illustration. Note: Covariates are ordered according to their unadjusted mean difference.

Table 4
Effects of collective action and spatial determinants of environmental income and dependency (CBPS weighted sample).

	Income		Dependency
	Selection	Quantity	
Intercept	0.598 (0.379)	0.563 (0.774)	0.216 (0.736)
Collective action			
Conservancy member	0.185 (0.112)·	0.520 (0.193)**	0.200 (0.210)
Other Controls			
Spatial determinants	Yes		
HH Characteristics	Yes		
Shock & wildlife conflict	Yes		
Distances	Yes		
invMillsRatio	3.691 (1.543)*		
logLik	−409.969		−199.783
Num. obs.	633	309	633
R^2		0.874	
Adj. R^2		0.864	
RMSE		0.751	

Note: full model estimates in S10.
***p < 0.001, **p < 0.01, *p < 0.05, ·p < 0.1.
Robust SE clustered at village level for fractional logit are provided.

sure to such opportunities, we use below and above median Euclidean distance to tourist accommodations, such as lodges and campsites to subset our sample and re-run double hurdle and fractional model estimations. Results are presented in Table 5.

In relative proximity to tourism accommodation, association of HH conservancy membership with environmental income and dependency are positive and effect sizes are large. HHs are 51 % more likely to engage in environmental product collection and generate 88 % more income from the environment. Tourism exposed conservancy HHs are also 66 % more dependent on the environment. Outside tourism areas, on the other hand, conservancy members tend to be 90 % less environmentally dependent than non-conservancy members. Hence, conservancy membership seems to be fostering environmentally oriented livelihood strategies, but only when HHs are in relative proximity to tourism, which requires relatively undisturbed landscapes (Meyer et al., 2021). These undisturbed and pristine landscapes can be found at most waterfronts and surrounding areas of lodges and campsite in the Zambezi region. As expected (see section 2), social capital indicators do not seem to be affected by this contextual moderation effect (S16) with unweighted results being qualitatively similar (S12).

In the subsample of HHs with low or no exposure to tourism opportunities, higher SOC and corresponding agricultural suitability is associated with lower levels of environmental income and dependence of HHs. HHs in this subsample have 39 % higher agricultural income, which corroborates our hypothesis. Controlling for potential confounders, conservancy members exposed to tourism boast significantly lower agricultural income (See S17, column 2 for OLS and S18, column 2 to 4 for double hurdle and fractional logit model results). Results are less explicit for HHs with low or no exposure to tourism opportunities, which may have been a consequence of the drought experienced during the survey period, which haunts the Zambezi region frequently (See S17, column 3 for OLS and S18, column 5 to 7 for double hurdle and fractional logit model results).

5.5. Robustness checks

To gain confidence in our results, we conduct three additional robustness checks. First, we estimate a standard Tobit model for determinants of environmental income to check whether our main

Table 5
Effects of collective action and spatial determinants of environmental income and dependency in tourism and non-tourism areas (CBPS weighted sample).

	Selection	Quantity	Depen dency	Selection	Quantity	Dependency
	Tourism Area			*Non-Tourism Area*		
Intercept	−0.184 (0.480)	−0.233 (1.315)	−0.862 (1.958)	3.071 (0.600)***	3.295(1.035)**	5.286(1.490)***
Collective action						
Conservancy member	0.511(0.142)***	0.880(0.433)*	0.656 (0.325)*	−0.199 (0.140)	−0.076 (0.206)	−0.899 (0.447)*
Spatial covariates						
Nightlight change	0.042 (0.037)	0.033 (0.046)	−0.059 (0.120)	0.037 (0.046)	−0.140 (0.050)**	−0.089 (0.122)
SOC	0.029 (0.021)	0.075 (0.027)**	0.028 (0.057)	−0.060 (0.028)*	−0.010 (0.041)	−0.173 (0.092)$^{\cdot}$
Biomass change | 1500 m Buffer	0.004 (0.011)	−0.001 (0.011)	0.009 (0.018)	−0.003 (0.011)	0.004 (0.011)	0.007 (0.023)
Other Controls						
HH Characteristics	Yes					
Shock & wildlife conflict	Yes					
Distances	Yes					
invMillsRatio		2.375 (1.343)$^{\cdot}$			−0.204 (1.104)	
logLik	−269.243		−111.772	−265.595		−84.908
Num. obs.	317	165	317	316	144	316
R^2		0.885			0.896	
Adj. R^2		0.865			0.876	
RMSE		0.813			0.954	

Source: own illustration.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$.
Robust SE clustered at village level for fractional logit are provided.

findings are driven by model specification. Results are reported in S7 and confirm the findings presented in Section 5.1.

Second, to assess whether the results from post-matching regression are robust across matching specifications we compare the covariate balancing propensity score weighted ATT with propensity score estimates using inverse probability weighting (ipw), implemented in the R package *ipw* by van der Wal & Geskus (2011) and nonparametric nearest neighbor matching, implemented in the R package *MatchIt* by Ho et al. (2011). Alternative ATT estimates of the effect of conservancy membership on environmental income selection, quantity and dependency are consistent with our main findings (see S14).

Third, as potential autocorrelation of the dependent variable may influence estimation results, we tests for it using Lagrange Multiplier diagnostics for spatial dependence following Anselin (1988), implemented using *lm.Lmtests* of the R package *spdep*. In order to identify relevant interaction scales of HHs, we follow Avelino et al. (2016) and select scales that matches the decision-making unit, i.e. the unit that reflect how HHs interact with their neighbors. We use three different weights matrices to indicate HH neighborhood: short (0 m – 500 m), medium (501 m–1500 m) and far (1501 m–3000 m). These represent different scales of spatial interaction of the HHs with their environment for the KAZA TFCA by Mosimane et al. (2014), which we interpret also as relevant neighborhoods. All robust LM tests (SAR, SEM and SARAR) do not reject the null hypothesis of significant spatial autocorrelation in the dependent variable. Following Gibbons & Overman (2012), we thus do not expect additional or qualitatively different insights from adopting a spatial regression approach.

6. Discussion and conclusion

To make ends meet, poor rural HHs rely on scarce environmental resources, which are often subject to open-access regimes. CBNRM schemes seek to overcome the commons dilemma inherent in many such resource use systems. We currently lack counterfactual-based evidence on the role of CBNRM in affecting how rural households interact with their environment under varying economic and ecological contexts. This paper examines contextual determinants of environmental income and shows that community conservancies in Namibia's Zambezi Region have produced heterogeneous patterns of environmental income and dependency depending on exposure to income opportunities from wildlife tourism.

In our sample of Namibian HHs, gross income from the environment accounts for about 13 % of total gross income on average, with poorer HHs being more dependent. This is in line with findings of Cavendish (2000), Kamanga et al. (2009) and Angelsen et al. (2014). HHs generally follow a multi-livelihood strategy with an average of 2.67 different income sources, similar to findings by Nielsen et al. (2013).

We find that HHs in conservancies are 19 % more likely to collect environmental products such as firewood, fish or devil's claw and generate on average 52 % more environmental income than households that are not members in such formalized CBNRM schemes. Conservancy membership is a less reliable predictor of environmental dependency, but the effect size (20 %) is relevant. In earlier work, also based on detailed environmental income accounting, Angelsen et al. (2014) and Ojeda Luna et al. (2020) fail to detect any statistically significant effect of collective forest management on forest income. Our result differs in that we do find a higher probability to select and generate quantity of environmental income. This difference may be explained by our counterfactual-based empirical approach and the regional focus: Angelsen et al. (2014) do not adopt a quasi-experimental identification strategy and their global study excludes Namibia. Ojeda Luna et al. (2020) look at rainforest users in Ecuador, a very different bio-geographical context from Namibia's Zambezi region.

Importantly, earlier work largely focusses on average impacts of collective natural resource management, which could have masked contextual moderation effects. In the Namibian context, we find that CBNRM has different effects on environmental income depending on whether HHs are exposed to wildlife tourism ventures. This is in line with Meyer et al. (2021) who found Namibian conservancies to work in favor of the region's woodland resources only when wildlife presence serves as a potential attractor for national and international tourism. Our result here corroborates this finding by showing that HHs in these areas are also more often and intensively engage in livelihood strategies that rely on the environment. A similar observation is reported by Ojeda Luna et al. (2020) for a rainforest environment in Ecuador, where tourism is not primarily wildlife-oriented. In our study region, however, conservation has historically had an almost exclusive focus on wildlife. In combination with Meyer et al. (2021), our finding suggests that wildlife tourism can have positive externalities on vegetation biomass (and thus carbon sequestration) and that this effect is driven by synergies in local people's livelihood choices, rather than just being a result of tourism enterprises selecting into particular landscapes. This potential causal pathway warrants future research, including on whether the average results are driven by effects of particular conservancies.

If HHs in areas that provide wildlife tourism opportunities engage more in environmental income generation, do they cut back on other income sources? Community conservation involves establishment of management zones, which (at least *de jure*) exclude certain land uses, especially agriculture (Mbaiwa, 2011). We find mean income from agriculture in relative proximity to tourism accommodation to be 39 % lower than outside these areas and 23 % lower than average income from agriculture. This result also holds when controlling for potential confounders (see S17 and S18). While conservancy members seem to implement the CBNRM restrictions more rigorously, this is not necessarily a result of differentials in social capital or trust (see results in S16). Instead, real or expected economic opportunities by conservancies also seem to provide sufficient private or collective incentives to align livelihood choices with conservation objectives. Outside areas that offer tourism benefits, such pro-environmental incentives may be inferior to agricultural opportunity costs.

Our approach to causal inference is enhanced by integrating household survey data with spatiotemporal predictors following Watmough et al. (2019) and Yeh et al. (2020) who show that remote sensing products improve rural poverty predictions. Our results suggest that remotely sensed SOC as an indicator of agricultural suitability (Yamano & Kijima, 2010), is associated with lower levels of environmental income and dependence of HHs. We also find changes in nightlight radiation to be associated with environmental income (or the lack thereof). This is in line with findings of Chen & Nordhaus (2011) who show that luminosity data can serve as a proxy for economic activity at the country level. Surprisingly, we find no robust relationships between vegetation biomass and environmental income, while ensuring that we compare CBNRM members with non-members exposed to similar biomass levels (represented by woodland cover) prior to CBNRM establishment. Pritchard et al. (2019) report similar findings for neighboring Zimbabwe and argue that HHs can generate income from vegetation biomass even on ecologically degraded lands by drawing upon kin and social networks, which facilitate access to resources beyond village borders. Such coping strategies would arguably come with additional transaction costs vis-à-vis households with better access to woodland resources and thus should affect welfare outcomes and livelihood choices. Our results in Table 2 and S15 indeed suggest that social networks are positively correlated with environmental income, but not causally related to CBNRM membership. It thus seems that the relationship between natural resource endowment (including access) and rural household income requires further research including on the historical processes that determined today's settlement patterns.

Our results have implications for both nature conservation and rural development in the Zambezi Region and for the general debate on human-environment interactions and related tradeoffs (Barbier, 2010). For large conservation areas to be sustainable, including transboundary areas such as KAZA, implementers must provide spatially targeted incentives, especially in sub-regions where synergies between conservation and development turn in to tradeoffs. The importance of wildlife tourism for the provision of conservation incentives will likely also be affected by economic and infrastructure investments, such as in roads, bridges, and the expansion of the Walvis Bay-Ndola-Lubumbashi Development corridor (Kalvelage et al., 2020a). Moreover, rural and urban development in the Zambezi Region also increasingly results in pressure on natural resources due to growing cattle herds, which represent an important capital asset (Bollig & Vehrs, 2020). Related future tradeoffs may materialize, for example, in the form of wildlife-induced livestock damage also in the relatively well-preserved parts of the region and must be considered in both conservation and development strategies for the region.

At global scale, nature protection may increase rural welfare on average (Naidoo et al., 2019), but context-driven impact heterogeneity can still result in local livelihood strategies being incompatible with conservation. More research is needed into what this implies for local support to large-scale conservation initiatives like the KAZA TFCA.

7. Ethical clearance

The research project Collaborative Research Center 228: Future Rural Africa [TRR 228/1] has been granted ethical clearance by the Ethics Committee of the Medical Faculty of the University of Cologne at the 13th of March 2018, reference number 18–057.

CRediT authorship contribution statement

Maximilian Meyer: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Carolin Hulke:** Writing – original draft, Writing – review & editing. **Jonathan Kamwi:** Methodology, Software, Data curation. **Hannah Kolem:** Writing – original draft, Writing – review & editing. **Jan Börner:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

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. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2022.106042.

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