frontiers | Frontiers in Environmental Economics

TYPE Systematic Review
PUBLISHED 27 November 2024
DOI 10.3389/frevc.2024.1408794

OPEN ACCESS

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RECEIVED 28 March 2024
ACCEPTED 29 October 2024
PUBLISHED 27 November 2024

CITATION
Siltanu GT, Smith-Hall C and Walelign SZ (2024) What matters? A global meta-analysis of environmental income and reliance determinants.
Front. Environ. Econ. 3:1408794.
doi: 10.3389/frevc.2024.1408794

What matters? A global meta-analysis of environmental income and reliance determinants

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A recent body of literature has documented the importance of environmental income to rural households in the Global South. However, this literature has not been analyzed to establish which findings are robust—what determines rural households' absolute and relative environmental income? We conducted a meta-analysis using published articles that measured environmental reliance from the Web of Science, Scopus, WorldCat.org, and MPDI databases. We examined the effect of socioeconomic, demographic, and resource site proximity variables on environmental income and reliance. We applied a meta-regression approach and included moderator variables such as sample size, survey frequency, and the types of journal to control for variations in effect estimates and assess risks of biases. We analyzed 112 studies published between 1996 and 2021 that together surveyed about 52,000 households in 35 countries. The findings confirmed that environmental income matters in total household income: environment, forest, and non-timber forest product reliance were, on average, 25 ± 11%, 27 ± 16%, and 27 ± 16%. The level of reliance was moderated by region and the type of environmental products. On average, the proportions of significantly negative, positive, and statistically insignificant effect estimates were 25%, 18%, and 57%. All covariates, except distance to the resource sites, were weakly correlated with environmental income and reliance, indicating no globally robust covariates. Thus, policies and interventions should build on regional specificities.

KEYWORDS

covariates, effect estimates, forests, non-timber forest products, global comparative, household income surveys, systematic review

1 Introduction

Humans derive substantial benefits from environmental products and services (IPBES, 2022). Around 1.6 billion people live within five kilometers of a forest (Newton et al., 2016), and rural households in the Global South, on average, obtain 28% of total household income from environmental resources (Angelsen et al., 2014) with 81% of this coming from forests. In general, poor households rely more on environmental income than the less poor (Babulo et al., 2008; Dash et al., 2016; Jiao et al., 2019; Kar and Jacobson, 2012; Khosravi et al., 2017; Mamo et al., 2007; Rayamajhi et al., 2012; Shrestha and Bawa, 2014; Wei et al., 2017) while better-off households have higher absolute environmental income (Damania et al., 2020; Escobal and Aldana, 2003; Fikir et al., 2016; Jiao et al., 2019; Nakakaawa et al., 2015; Wei et al., 2017).[1] Environmental income is the value-added from raw and processed products extracted from wild and uncultivated natural resources, including environmental wages and payments for environmental services (Sjaastad et al., 2005). It includes non-forest environmental income and forest income. Environmental reliance—also called environmental dependence or relative environmental income—is the share of environmental income relative to the total income of households (Angelsen et al., 2014).

A large body of empirical research on the absolute and relative contributions of environmental income to rural livelihoods has emerged in the last two decades, enabled by the advancement of environmental data collection methods (Angelsen et al., 2011; Cavendish, 2002; FAO, 2016). These studies reveal that environmental income serves three primary functions for rural households: it helps meet current consumption, acts as a buffer against shocks and seasonal gaps, and enables asset accumulation and poverty reduction.[2]

All studies found that households use multiple products—such as fuelwood, construction materials including timber, fruits, vegetables, wild game, and medicinal plants—to support current consumption via subsistence or cash income (e.g., Adongo et al., 2019; Angelsen et al., 2014; Asfaw et al., 2013; Aye et al., 2019; Bierkamp et al., 2021; Dash et al., 2016; Furo et al., 2022; Heubach et al., 2011; Hlaing et al., 2017).

There are conflicting findings on the role of environmental products as safety nets for vulnerable households (Wunder et al., 2014). While some studies find a limited role (e.g., Møller et al., 2019), others have demonstrated that environmental income helps households, especially the transitory poor, to cope with shocks. For instance, Wunder et al. (2018) argued that households resort to forest product extraction when they experience crop failure due to adverse weather shocks, as forest extraction is more resilient to weather variation and less seasonal than crop production. Similarly, in a recent study in West Bengal, India, households increased their forest product extraction to deal with covariate shocks related to crop failure, flooding, and crop depredation by wildlife (Ray and Mukherjee, 2023). Moreover, a study in Malawi by Mulungu and Kilimani (2023) showed that access to forest resources enables households to avoid costly coping strategies such as consumption reduction and asset depletion that could have negative long-term consequences for their welfare.

While environmental income may play a role in reducing poverty (Jagger et al., 2022; Miller and Hajjar, 2020), empirical evidence is limited. The few studies using panel data have found weak evidence. Walelign et al. (2019, 2021) showed that environmental income had a limited impact on households' asset accumulation. However, they found that non-forest environmental income was significantly positively correlated with livestock asset accumulation (Walelign et al., 2019) and overall asset accumulation (Walelign et al., 2021). Furthermore, some rural households have been able to move out of poverty through forestry and forest products, although this is not a widespread phenomenon (Shackleton et al., 2007; Smith-Hall et al., 2022).

The use and importance of environmental resources thus vary across different contexts, such as geographic locations, time periods, and communities (Garekae et al., 2017; Razafindratsima et al., 2021). Within communities, there is also household-level heterogeneity in the degree of reliance and extraction of environmental products (e.g., Babulo et al., 2008; Jiao et al., 2019; Wei et al., 2017). Understanding these variations and the socioeconomic factors that influence them is crucial for designing effective and appropriate rural development policies to achieve sustainable resource management and poverty reduction (Furo et al., 2022; McElwee, 2008). The existing empirical evidence is mainly based on specific case studies with homogenous contexts and mixed and inconclusive results on the significance and direction of the effects of socioeconomic covariates. Systematic reviews and meta-analyses that synthesize and compare findings from different studies and contexts are lacking. The exception is Vedeld et al. (2007), who systematically reviewed 51 case studies published up to 2003 in 17 countries in the Global South. Angelsen et al. (2014) made use of advances in survey instruments and collected standardized data across multiple countries, providing a novel empirical analysis with a large sample size and cross-contextual insights.

Moving beyond these studies, we synthesized results from primary (empirical) studies over a 26-year period, providing the hitherto most analysis of the effect of socioeconomic factors on household environmental income and reliance.

The objective of the present study is twofold: to (i) quantify the degree of environmental reliance at the household level and (ii) investigate the influence of socioeconomic variables on environmental income and reliance. This is done using a meta-analytical approach encompassing 112 primary studies up to the year 2021, adhering to Page et al. (2021) guidelines. We extracted 91 relative income estimates pertinent to the first objective and 915 effect estimates relevant to the second objective.

The paper is structured as follows: in Section 2, we describe the methods—how we searched, compiled, coded, and analyzed the data and the robustness of the results. Section 3 presents the descriptive and meta-regression results. In Section 4, we interpret the results, followed by concluding remarks and recommendations for future studies in Section 5.

2 Methods

2.1 Literature search and compilation

We systematically searched for and selected empirical studies following Page et al. (2021) and Havránek et al. (2020). Figure 1 presents an overview of the process, and the number of articles included and excluded in each step. We included articles published in English that measured environmental reliance and employed a quantitative analytical method to establish statistical inferences between socioeconomic variables and environmental income and

1 Notable exceptions are Li et al. (2021) and Uberhuaga et al. (2012), who reported that non-poor households earn a higher absolute income and rely more on environmental resources than poor households.

2 Miller and Hajjar (2020) added a fourth function focused on pathways to prosperity. This function is primarily focused on non-economic elements–such as education, governance, and culture–and hence not included here.

reliance. We focused on the age, education, gender of the household head, household size, and distance to the resource site (henceforth called target covariates), as these were frequently and relatively consistently used in the primary studies. The authors discussed and decided on three groups of keywords separated by inter and intra-group Boolean connectors of "OR" and "AND": (forest OR environmental OR "non-timber forest products[3]"), (income OR dependence OR reliance OR livelihood), and (regression OR estimation OR model). The authors also discussed and decided what databases to use for the literature search and developed the screening and data extraction tools. We searched the Web of Science, Scopus, WorldCat, and MDPI. The first two were selected due to their comprehensive coverage of journals, and the last two to capture articles not indexed by the former databases.

We used query strings "TI = ((forest OR environmental OR "non-timber forest products") AND (income OR dependence OR reliance OR livelihood)) AND TS = (regression OR estimation OR model)," "Title ((forest OR environmental OR "non-timber forest products") AND (income OR dependence OR reliance OR livelihood)) AND All (regression OR estimation OR model)," and "TI ((forest OR environmental OR "non-timber forest products") AND (income OR dependence OR reliance OR livelihood))" for Web of Science, Scopus, and WorldCat; where TI is title, and TS is topic. For MDPI, we entered the keywords separately, for instance, "Title (environmental AND income) AND All fields (regression)," entering 36 simplified keyword combinations to address all the keywords. After several keywords and Boolean connector combination trials, the search was conducted on June 7, 2021.

We identified 2,920 documents from the four databases, resulting in 2,123 articles written in English, excluding books, book chapters, working papers, abstracts, magazines, and encyclopedia articles. We excluded 717 duplicates and 1,048 titles on research themes other than environmental income and reliance through title screening, providing 358 papers. Of these, 14 could not be located, and 261 focusing on plantation, cultivation, afforestation, agroforestry, agriculture, and environmental valuation, or only considering total household income as a dependent variable, were excluded. We used the remaining articles to add 38 articles from their citations, resulting in 121 papers. Lastly, we excluded nine papers: in one study, the regression result table was the exact copy of a previously published study in another country; the dependent variables in four studies were not environmental income or reliance, and four articles neither considered the target covariates in their regression analysis nor calculated relative income. Of the final total of 112 studies, 71 quantitatively examined the relationship between target covariates and environmental income and reliance and measured the average relative environmental income; 35 only related covariates with the outcome variables, and six articles only computed the average relative environmental income (Supplementary Table 1). The first author undertook the screening and data extraction under the supervision of the second and third authors.

3 While we prefer the term environmental product to non-timber forest product (NTFP), the latter has been commonly used in the literature and is hence employed here. For a discussion of terminology, see Smith-Hall and Chamberlain (2023).

2.2 Coding

The studies were diverse in their method of analysis, measurement scale, choice of explanatory variables, and currency used to calculate household income. Therefore, we only considered the sign and significance level with some calibrations to standardize the sign of coefficients for the effect estimates analysis.

In the case of the gender of the household head, we extracted 175 coefficients (male-headed for 90 coefficients and female-headed for 85). We dropped nine coefficients since we could not determine which gender the sign referred to. To standardize the effect of gender on environmental income and reliance, we adjusted the male-headed households' coefficients into female-headed by multiplying the coefficients by a negative one. This transformation is robust. A robustness check showed a slight change in only the magnitude of the intercept. Therefore, we generated 175 coefficients for the gender variable described as female-headed (Supplementary Table 14).

Most studies measured household head education in years. However, some studies measured household education as a dummy or category, such as the percent of educated household members or mean education, maximum education, number of educated men per household, or the average education of adult household members. We included household head education in years and household head education measured as a dummy. The other coefficients were dropped as they were not comparable to the education of the household head, or it was challenging to identify the sign and significance level for multiple coefficients.

Similarly, household size was measured differently. Coefficients based on only the number of male and female workers, the number of dependents or dependent ratio, or the number of adult laborers were dropped as these differ from the adult equivalent unit and are not comparable to household size based on all household members.

In almost all studies, the distance variable was measured in kilometers and minutes of walk from the house to the resource site. However, a few studies measured distance as far and near, and we included those coefficients.

In most studies, age was measured in years. However, a few studies considered the average age of the household. Others measured it categorically in different age groups or as a dummy of old and young household heads. We considered coefficients only when age was measured in years and a dummy because it was easier to identify the effect. We also considered the age-squared coefficient as a moderator variable.

We combined the signs and statistical significance levels of the covariates' coefficients as effect estimates for the meta-analysis. This approach was necessitated primarily by two limitations: firstly, the heterogeneity of estimation methods across primary studies, coupled with the lack of comprehensive data such as the standard deviations of both dependent and independent variables, precluded the standardization of coefficients to a unified effect size. Secondly, the diversity in reporting metrics—such as log odds and marginal effects—among various studies rendered the standardization of

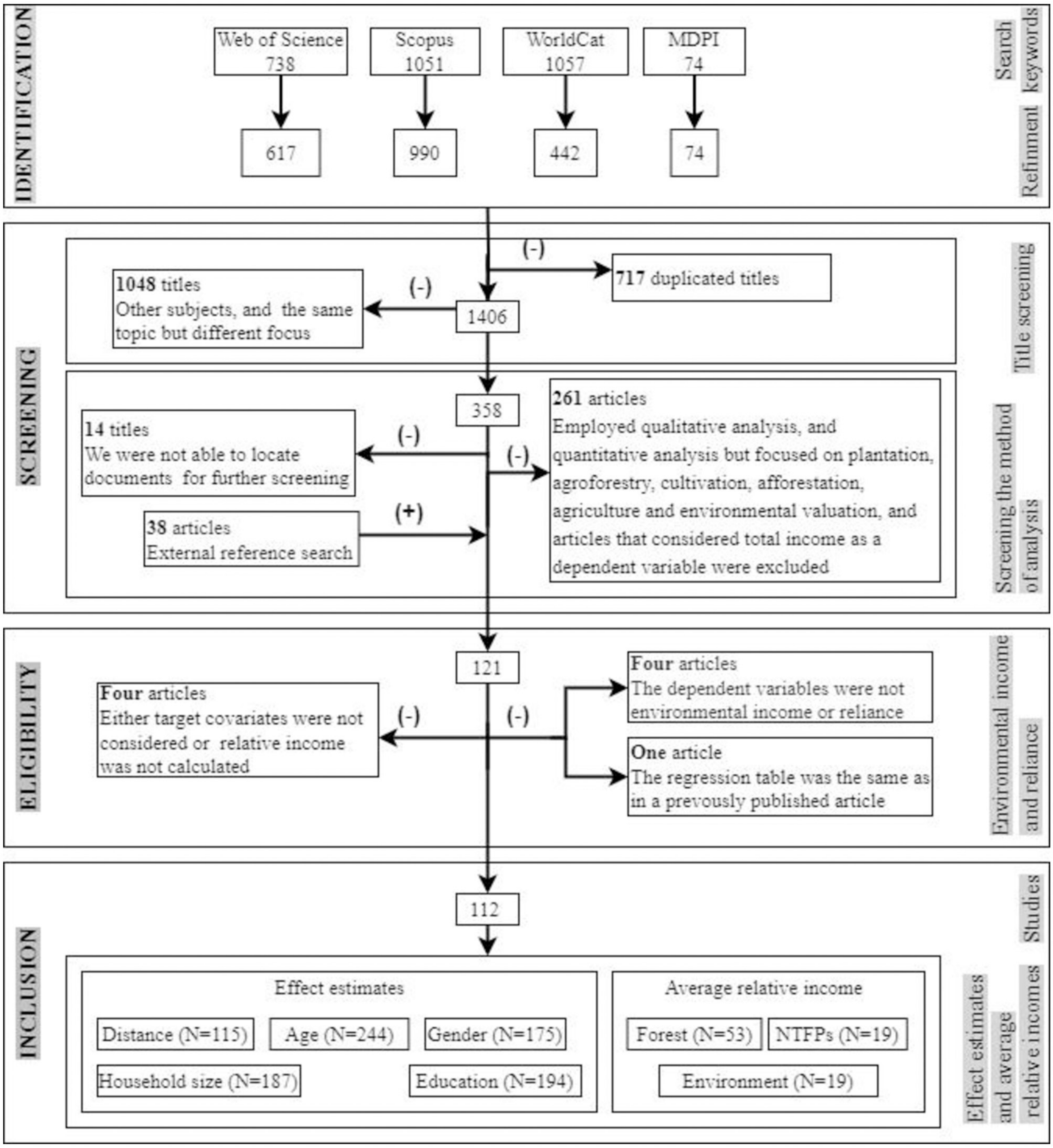

FIGURE 1
The flow of steps taken to select documents included in the meta-analysis adapted from Page et al. (2021).

coefficients to a singular effect size impracticable, even when estimation models were analogous (Card et al., 2010; Waldorf and Byun, 2005; Wehkamp et al., 2018). Thus, based on the signs and the significance levels of the coefficients, we categorized the effect of the target covariates into three groups: negative effect when the coefficient is negative and significant; positive effect when it is positive and significant; and non-significant when the coefficient is either positive or negative but statistically insignificant. The empirical studies reported p-values of 0.01, 0.05, and 0.1 to determine the significance level of covariates. We assumed the significance level of 0.1 as the threshold between significant and non-significant. Accordingly, we generated a total of 915 effect estimates. We also categorized the effect of covariates into positive and negative, irrespective of the significance level, to capture the directional effect on environmental income and reliance.

Many studies reported the proportion of the average relative environment, forest, or NTFP income. Some studies reported the relative income separately in terciles, quartiles, quintiles, or other subgroups. When the respective sample size was reported, we multiplied the relative income by the corresponding observations, summed and divided by the total observation. However, more than 86% of the studies that estimated the relative environmental income did not report the standard deviation or the standard error. It was also not possible to calculate the average absolute income, preferably in USD purchasing power parity (PPP) for a specific year, as (i) the currency used was not explicitly stated in 25% of the studies; (ii) 17% of studies did not report the data collection year; and (iii) the average absolute income was reported in units (per household, per capita, per adult equivalent unit) that we could not standardize given the available data.

2.3 Data analysis

2.3.1 Moderator variables

In our meta-regression analysis, the outcome variables are the average relative environmental income and the effect estimates (effect categories). In addition, we included moderator variables to explain variation in the dependent variables. We broadly categorized moderator variables into four groups: categorical covariates (age, education, distance, gender, and household size); regional variables (Africa, Asia, and Latin America); methodological variables (age-squared, survey frequency, income aggregation, estimation models, and sample size), and publication variables (publishing journals and publication year). The moderator variables are defined in Table 1.

2.3.2 Multiple linear regression model

We fit a multiple linear regression model to explain the effect of moderator variables on the variations in the average relative environment, forest, and NTFP income. NTFP income is defined as income earned from all products or services produced in the forest, excluding timber (Heubach et al., 2011). In comparison, forest income includes income from timber and non-timber forest products. Environmental income is derived from uncultivated forest and non-forest environmental resources (Sjaastad et al., 2005). The multiple regression model for the average relative forest income (ARFI) is:

$$\begin{aligned} ARFI_i = \beta_0 + \beta_1 lnSample_i + \beta_2 Year_i + \beta_3 Asia_i \\ + \beta_4 Latin\ America_i + u_i \end{aligned} \tag{1}$$

where βs are parameters, u_i is the error term, and the explanatory variables are explained in Table 1. We adjusted the publication year in reference to 1995 by subtracting the reference year from each observation and transformed the sample size into logarithm form to control the noise.

Since the number of observations for the average relative environment and NTFP income is small for multiple regression, we pooled the different relative incomes from the environment, forest, and NTFPs to form the merged average relative income (ARI). Therefore, besides the moderator variables in Equation 1, a dummy for NTFP and forest is included in the model. The ARI model is specified as:

$$\begin{aligned} ARI_i = \beta_0 + \beta_1 lnSample_i + \beta_2 Year_i + \beta_3 Asia_i \\ + \beta_4 Latin\ America_i + \beta_5 NTFPs_i + \beta_6 Forest_i + u_i \end{aligned} \tag{2}$$

For both Equations 1, 2, we first ran the ordinary least squares (OLS) (Supplementary Table 2). However, the models were heteroscedastic as (i) the quantile-normal distribution plot and the kernel density estimates indicated the presence of outliers, and (ii) the robust Mahalanobis distance detected bad and good leverage points and vertical outliers. As the OLS led to biased and inefficient estimates (Supplementary Figure 1 and Supplementary Table 2), we fitted the robust regression model (MM-estimator), which accommodated outliers with a high breakdown point and a Gaussian efficiency of 70% (Verardi and Croux, 2009).

2.3.3 Multinomial logit model

We employed a multinomial logit (MNL) model to determine the effect of moderator variables on the variation of effect categories, as these categories (coded as significant positive, non-significant, and significant negative) are nominal outcomes. Let y denote the effect categories, and x denote a vector of moderator variables. The MNL, estimating the probability of effect categories j given the moderator variables, can be specified as:

$$\Pr(y = j|x) = P_{ij} = \frac{e^{(\theta_j + x_i \beta_{j|2})}}{\sum_{j=1}^{3} e^{(\theta_j + x_i \beta_{j|2})}} \tag{3}$$

Where θ_j is the intercept for the j's category, β is the vector of parameters, x_i is the vector of moderator variables, and "2" is the base category (non-significant effect) for normalization. The signs of parameters are interpreted by comparing the estimated coefficients with the base category.

2.3.4 Publication bias

Publication bias is a sample selection bias when studies with statistically insignificant findings are less likely to be accepted for publication or not submitted by researchers (Nelson and Kennedy, 2009). To check for publication bias, we used an approach employed by Card and Krueger (1995), as the conventional funnel plot approach is not appropriate in discrete outcome models (Wehkamp et al., 2018). Card and Krueger (1995) argued that there is a direct proportion between the absolute t-value and sample size in the absence of a publication bias based on the assumption that a large sample size increases the probability of obtaining either significantly positive or negative effect estimates (Card et al., 2010). Therefore, after linearly regressing the log-transformed absolute t-value against the log-transformed sample size, we tested the parameter (H_o: $\beta = 1$ against H_1: $\beta \neq 1$) (Waldorf and Byun, 2005). Accordingly, rejecting the null hypothesis indicates the presence of publication bias.

2.3.5 Evaluating the meta-regression analysis

A robustness check is essential to examine the genuine influence of variables. Therefore, we checked for the robustness

TABLE 1 Description of moderator variables.

Variables	Definition
Categorical covariates	A group of five categorical variables: age, education, distance, gender, and household size. Based on their influence on absolute environmental income (AI) and relative environmental income (RI), they were divided into ten categorical variables: age (for AI and RI), education (for AI and RI), distance (for AI and RI), gender (for AI and RI), and household size (for AI and RI), where age (for AI) is a reference variable
Regions	A group of three categorical variables: Africa, Asia, and Latin America, where Africa is a reference variable
Survey frequency	A dummy variable assigned "1" if households were surveyed more than once, "0" if it was a once-off annual recall period
Age-squared	A dummy variable that is "1" if age-squared was included in the regression as an explanatory variable, "0" otherwise
Aggregate income	A dummy variable that is "1" if the dependent variable was aggregated as environment or forest income or reliance, "0" otherwise
Models	A group of three categorical variables: linear, discrete, and censored models, where the linear model is a reference variable
FEW journals	A dummy variable that is "1" if the article was published either in Forest Policy and Economics, Ecological Economics, or World Development (FEW), "0" otherwise
Sample size (ln)	The log transformation of the number of observations (sample size) used in the estimation
Publication year	The year the article was published in reference to 1995

of categorical covariates and the moderator variables, focusing on the coefficients' signs, significance level, and stability. We adopted two techniques (Card et al., 2010; Wehkamp et al., 2018). First, we increased the number of observations by incorporating those effect estimates that were measured in the probability of participation in environmental resource utilization or the quantity of extraction (thus increasing N from 689 to 915; Supplementary Table 3 and categories 9 and 10 in Table 3). Then, we fitted two separate binary logit models, one containing the negative and statistically insignificant effects and the other the positive and statistically insignificant effects, to check the influence of the number of effect categories and observations (Wehkamp et al., 2018). Second, we ran a logit model for the negative and positive effect categories irrespective of the significant level (Supplementary Table 7).

3 Results

3.1 Descriptive results

The empirical studies were published in 54 journals from 1996 to 2021 and cited 8,250 times as of June 7, 2021. Most studies were conducted in Asia (49%), followed by Africa (39%) and Latin America (11%). The average sample size was 671 ± 1,253, ranging from 30 to 7,360, with 76% of studies using a once-off annual recall period and 24% a shorter period (weekly, monthly, quarterly, three, or two times a year).

The empirical studies were diverse in their model specification, choice of explanatory variables, and measurement of dependent variables. The dependent variables were measured as absolute (37%) and relative (38%) income, probability of participation in resource extraction (21%), or quantity of extraction (4%) (Table 3). Studies, on average, estimated the effect of 12 explanatory variables (including the target covariates), with 43% employing linear models (OLS and its extensions), 24% discrete choice models (binary logit, probit, and multinomial logit), and 33% censored and truncated models (Tobit and Heckman-selection models). Most studies did not provide information about the strength of the relationship between the covariates and the dependent variables. Around 60% of the studies that employed linear models reported R-squared, and 25% of the non-linear model studies reported pseudo-R-squared. The means of R-squared, adjusted R-squared, and pseudo-R-squared were 0.39, 0.36, and 0.26 (Table 2).

3.1.1 The average relative environmental income

On average, environmental income contributed about 25% of the total income of households in the Global South; the estimates for the share of forest and NTFP income were both 27% (Table 2). This is unexpected as NTFP income is a subset of forest income, and the latter is also a subset of environmental income. Comparing sample size across types of relative income shows that relative NTFP income was derived from studies with a small sample size with a smaller standard deviation, while the relative environment income was derived from studies with a large sample size and a higher variation among studies (Supplementary Figure 2). Besides, studies focusing on forests, especially on NTFPs, may be biased toward surveying households that rely more on environmental resources. Studies also apply different definitions for environmental income, forest, and NTFPs.

3.1.2 The effect estimates

The primary studies ($N = 106$) ran 288 regressions and determined 915 effect estimates. More than 75% of the effect estimates explained absolute and relative environmental income and 25% the probability of participation in environmental resource extraction or quantity of extraction (Table 3). Of the total of 915 effect estimates, 57% ($N = 517$) were non-significant, while 25% (229) and 18% (169) were negative and positive (Table 2). When we exclude effects on the probability of participation in environmental resource extraction or quantity of extraction ($N = 226$), the negative effect was almost unaltered ($N = 171$), the non-significant effect increased to 59% ($N = 407$), and the positive effect declined to 16% ($N = 111$) (Supplementary Figure 3). The sum of negative and positive effects proportions was lower than that of the statistically

TABLE 2 Summary statistics for the studies ($N = 112$) included in the meta-analysis.

Variables	N	Effect categories (%)			
		Negative	Non-significant	Positive	
Target covariates	915[a]	25.03	56.50	18.48	
Age	244	23.36	64.75	11.89	
Gender	175	21.14	64.00	14.86	
Education	194	28.87	57.73	13.40	
Household size	187	15.51	51.87	32.62	
Distance	115	43.48	33.04	23.48	
Average relative income (%)		**Mean**	**Std. dev.**	**Min**	**Max**
Environment	19[b]	25.34	10.51	8.20	58.00
Africa	4	28.28	5.57	20.00	32.00
Asia	9	23.83	5.09	14.00	33.00
Latin America	6	25.63	18.06	8.20	58.00
Forest	53[b]	27.18	15.78	3.60	80.00
Africa	17	32.54	14.68	17.90	80.00
Asia	26	22.98	12.80	3.60	43.00
Latin America	10	28.98	22.17	9.00	74.50
NTFP	19[b]	27.12	15.84	4.85	54.04
Africa	8	26.79	14.63	8.00	47.00
Asia	10	25.00	16.34	4.85	54.04
Latin America	1	51.00			
Moderator variables					
Asia	921	0.476	0.500	0	1
Latin America	921	0.176	0.381	0	1
Survey frequency	915	0.232	0.422	0	1
Age-squared	915	0.129	0.335	0	1
Absolute income	689[a]	0.496	0.500	0	1
Aggregated income	689	0.682	0.466	0	1
Linear models	915	0.426	0.495	0	1
Censored models	915	0.239	0.427	0	1
FEW journals[e]	921	0.489	0.500	0	1
Sample size	909	671	1,253	30	7,360
Publication year	112[d]	2,014	6	1,996	2,021
Descriptive variables					
Absolute and relative incomes	915	0.753	0.431	0	1
R-squared	78[c]	0.391	0.189	0.09	0.81
Adj. R-squared	56[c]	0.355	0.181	0.08	0.70
Pseudo R-squared	39[c]	0.264	263	0	0.93
Explanatory variables	288[c]	12	5	2	29
Impact factor	104[d]	0.971	0.601	0.151	2.52
Citation	112[d]	74	129	0	766

N is observations, [a]effect estimates, [b]average relative income, [c]regressions, [d]studies, and [e]see definition in Table 1.

TABLE 3 Categories of dependent variables based on their measurements and the corresponding effect estimates and effect categories.

Category	Dependent variable	N	Regressions	Effect estimates	Effect categories		
					Negative	Non-significant	Positive
1	Absolute environmental income	14	29	103	26	60	17
2	Relative environmental income	12	16	60	20	34	6
3	Absolute forest income	29	44	144	46	79	19
4	Relative forest income	29	48	163	35	93	35
5	Absolute NTFP income	12	16	40	6	27	7
6	Relative NTFP income	10	13	42	4	34	4
7	Absolute environmental product income[a]	9	25	55	11	35	9
8	Relative environmental product income[a]	7	29	82	23	45	14
9	Quantity (in units, numbers, type of species, or frequency) of extraction	7	16	38	7	20	11
10	Probability of participation in resource extraction	25	52	188	51	90	47
	Total	154[b]	288	915	229	517	169

N is the number of dependent variables in each category; [a]absolute or relative environmental product income refers to forest and non-forest environmental products (e.g., medicinal plants, thatch, fodder, fuelwood, game meat, fruits, construction poles, caterpillar fungus, and spice) where the income or reliance level is not aggregated; [b]45% of studies examined more than one dependent variable (category).

insignificant effects except for distance. The positive effect was higher than the negative effect only for household size.

We also analyzed the proportion of negative and positive effects reported by primary studies irrespective of their significance level across covariates (Figure 2a). The proportion of negative effects, except for household size, on environmental income and reliance was predominant, with approximately 65% ($N = 158$) for age, 63% ($N = 110$) for gender, 68% ($N = 131$) for education, 69% ($N = 79$) for distance, and 36% ($N = 67$) for household size. These findings, on average, suggest a trend where younger individuals, male heads of households, those with lower educational levels, residents in closer vicinity to resources, and larger households have a propensity to rely more on environmental resources and accrue greater absolute environmental income. A more detailed examination of the data segmented into absolute and relative income reveals additional insights (Figure 2b). Notably, as distance to the resource site increases, reliance on environmental products decreases with a proportion of 83% ($N = 33$). Conversely, female-headed households demonstrate a markedly lower rate of absolute environmental income at 22% ($N = 15$), while younger households show a slight increase to 69% ($N = 64$) in absolute income generation.

3.2 Meta-regression results

3.2.1 The effect of moderator variables on the variation of environmental reliance

The robust regression results (Table 4) show that both sample size and the Latin America region significantly negatively affect ARFI and ARI, which are measures of the relative contribution of environment, forest, and NTFP income to total income. Specifically, a one percent increase in sample size was associated with a 0.08% and 0.05% decrease in ARFI and ARI, respectively. This suggests that studies with smaller sample sizes tended to report higher average relative income. Moreover, compared to Africa, the Latin America region had lower ARFI and ARI by about 20% and 16%, respectively. Studies also reported a lower level of environmental reliance in Asia than in Africa, but this difference is statistically insignificant. The NTFP dummy variable significantly

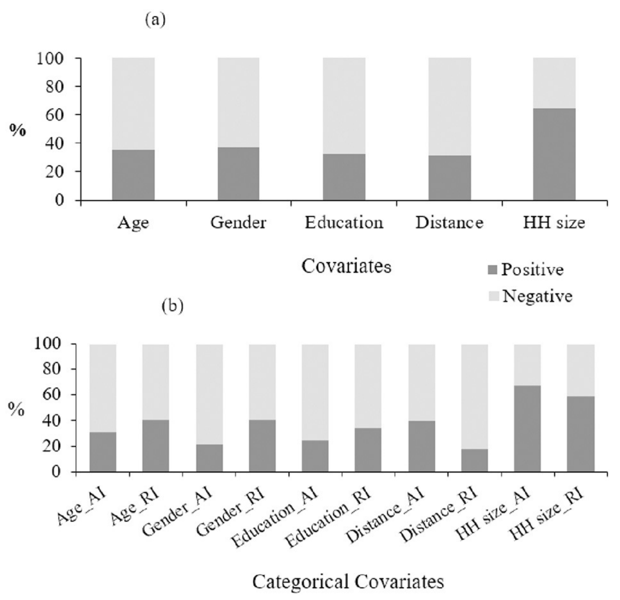

FIGURE 2
Proportion of positive effects of covariates regardless of the significance level. **(a)** The proportion of the negative and positive effects of covariates on AI, RI, and probability and quantity of environmental resource extraction, and **(b)** the proportion of the negative and positive effects of covariates on AI and RI, disaggregated.

TABLE 4 Robust regression results of average relative forest income (ARFI) and average relative income (ARI) against moderator variables[a].

Moderator variables	ARFI	ARI
Sample size (ln)	−0.081***	−0.048***
	(0.025)	(0.016)
Publication year	0.008	−0.001
	(0.009)	(0.003)
Asia	−0.089	−0.011
	(0.058)	(0.026)
Latin America	−0.202***	−0.164***
	(0.052)	(0.022)
NTFPs		0.109***
		(0.025)
Forests		0.033
		(0.036)
Constant	0.648***	0.567***
	(0.053)	(0.129)
Observations	50	85

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; standard errors in parentheses; [a]six variables from Table 1 are not included here as they were (i) not applied for relative environmental income, and/or (ii) the number of observations was too small (as a rule of thumb, we applied a 1:10 ratio of explanatory variable to observations Green, 1991).

positively affects ARI, indicating that NTFP income accounted for a larger share of total income than environment income. The coefficient of the NTFP dummy implied that a change from average relative environment income to NTFP income increased the ARI by around 11%. The publication year, a proxy for the year the study was conducted, was statistically insignificant. But, in both models, the magnitude is small, which may indicate the share of environmental income in households' total income remained similar over time.

3.2.2 The variation of effect categories

We depict the marginal effect results (Supplementary Table 4) and the predicted margins of categorical covariates across effect categories (Supplementary Table 5) based on the MNL results (Supplementary Table 6) in Figure 3. We also report the robustness check results in Supplementary Table 3, which confirmed the stability of the coefficients. The predicted marginal effects, which measure the vertical difference from one categorical covariate to another regardless of the variables' position, indicate the probability values at each trough, peak, and saddle point. Thus, the marginal effect reveals the difference in the predictive probability of categorical covariates with respect to the reference categorical variable and among all other variables. We do not compare inter-categorical covariates empirically as they come from different observations of the effect categories. However, we compare the effect of each covariate on absolute and relative environmental income to show how target covariates influence AI and RI.

A change in the effect of age (from AI to RI) and gender (from AI to RI) increased the average probability of a positive effect and decreased that of a negative effect, while for education and distance, the trend of positive and negative categories is the same (but in the reverse direction: growing probabilities for education and shrinking for distance). Although not many of the marginal effect results are statistically significant, the results show that age and gender could affect environmental income and reliance differently. The probability of a significant and negative age (for AI) effect indicates that, on average, AI decreases as the household head's age increases. We also ran a logit regression irrespective of the significance level and found comparable trends (Figure 4).

The only case where the average predicted probabilities of positive and negative effects were significantly higher than the statistically insignificant effect is for distance to the resource site (for AI), predicting the lowest probability of a statistically insignificant effect (24%). Moreover, the likelihood of a negative effect was higher than a positive effect for all categorical covariates except household size.

3.2.3 The influence of moderator variables on the variation of covariates' effect categories

We used the MNL results (Supplementary Table 8) to calculate the marginal effects of moderator variables, which are shown in Table 5. Supplementary Table 9 presents the results of the robustness check, which confirmed the consistency of the sign and significance levels of most moderator variables and their coefficients.

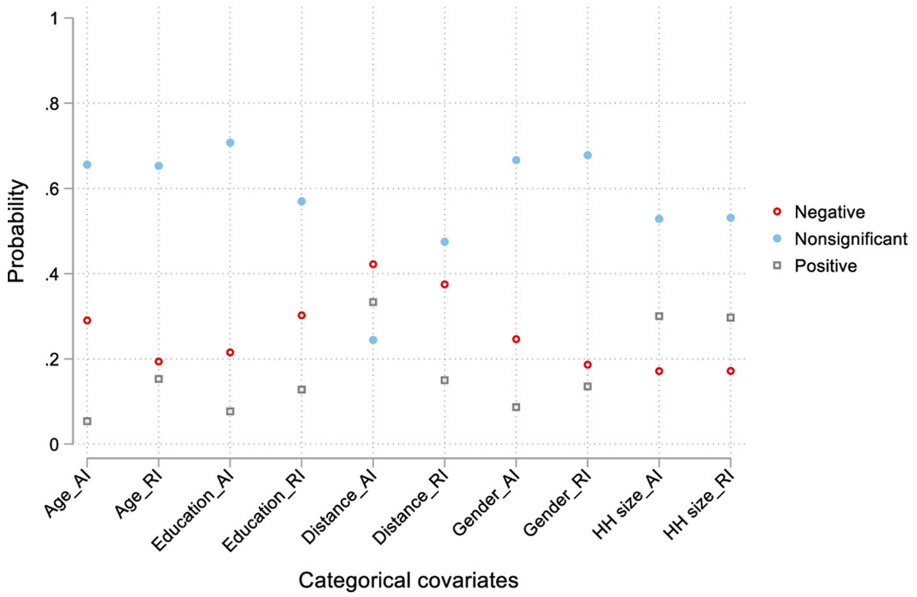

FIGURE 3
The average probability value of categorical covariates, differentiating by AI and RI.

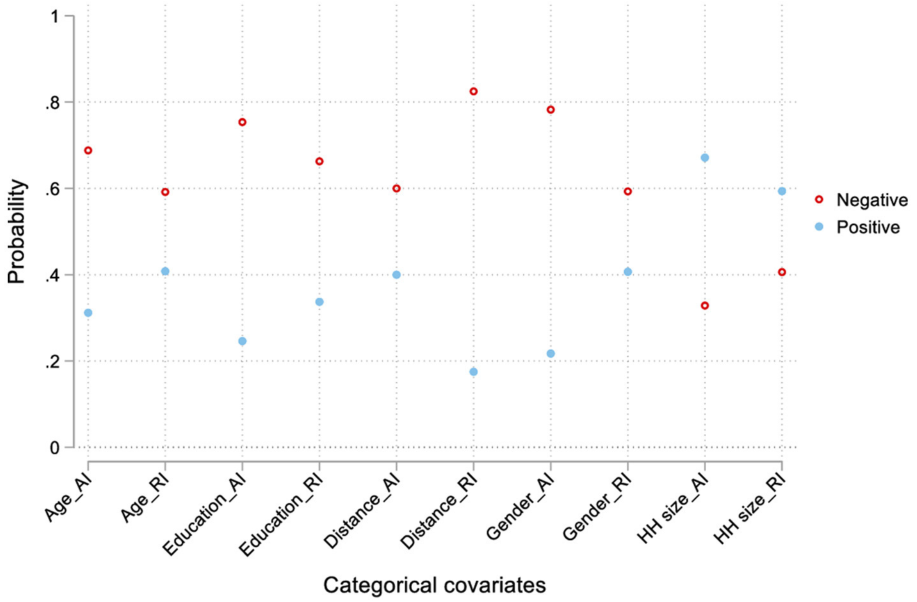

FIGURE 4
The average probability value of categorical covariates regardless of the significance level, differentiating by AI and RI. The graph is derived from the logit model (Supplementary Table 7, column 3).

The effect categories of the covariates varied across regions, as indicated by the regional categorical variables. However, the variation was not uniform across all covariates (Figure 5 and Table 5). Primary studies from Latin America tended to report more negative and fewer positive effects of covariates than studies from Africa and Asia, except for the effect of education. The difference was especially large for the age effect, where the likelihood of finding a negative effect increased by 18% to 41% compared to studies from Africa and Asia. In contrast, studies from Asia had a higher average predicted probability of a positive education effect of 16% and a lower probability of a statistically insignificant effect of 26% than studies from Africa. The probability of finding a negative gender effect was also higher by 16% in Asia than in Africa.

We did not find consistent patterns of methodological and publication variables affecting the variation in the effect categories.

TABLE 5 Marginal effects of moderator variables on the predicted probability of effect categories of covariates[a].

Variables	Age			Education		
	Negative	Non-significant	Positive	Negative	Non-significant	Positive
Age (RI vs. AI)	−0.063	−0.098	0.161***			
Education (RI vs. AI)				0.134	−0.175**	0.041
Asia vs. Africa	−0.004	0.004	0.000	0.104	−0.262***	0.158***
Latin America vs. Africa	0.400***	−0.271	−0.129**	−0.072	−0.042	0.114
Latin America vs. Asia	0.405***	−0.275	−0.130***	−0.177**	0.221**	−0.044
Survey frequency	−0.137	0.257**	−0.120***	0.032	0.013	−0.045
Age squared	−0.036	−0.093	0.129***			
Aggregate income	0.005	−0.125	0.120***	0.163**	−0.236***	0.073
Discrete vs. Linear models	−0.010	0.114	−0.105**	−0.115	0.063	0.052
Censored vs. Linear models	0.024	−0.016	−0.009	−0.098	−0.028	0.126*
Censored vs. Discrete models	0.034	−0.130	0.096**	0.016	−0.091	0.074
Journals	0.057	−0.026	−0.031	0.055	0.142*	−0.198***
Sample size (ln)	0.030	−0.111*	0.081**	−0.033	0.043	−0.010
Publication year	−0.063*	−0.048	0.111**	−0.060*	0.066	−0.006
Pr(y = j)	0.235	0.661	0.104	0.252	0.636	0.112

Variables	Distance			Household size			Gender		
	Negative	Non-significant	Positive	Negative	Non-significant	Positive	Negative	Non-significant	Positive
Distance (RI vs. AI)	−0.082	0.234*	−0.152						
Gender (RI vs. AI)							0.010	−0.053	0.043
Household size (RI vs. AI)				0.063	−0.053	−0.010			
Asia vs. Africa				0.007	0.078	−0.084	0.157**	−0.097	−0.059
Latin America vs. Africa				0.184**	0.027	−0.211	0.266**	−0.176	−0.090
Latin America vs. Asia				0.177**	−0.051	−0.126	0.109	−0.078	−0.031
Survey frequency				0.198*	−0.258**	0.060	−0.041	0.085	−0.044
Aggregate income	−0.058	0.284**	−0.226	0.021	−0.174	0.153	0.079	−0.078	−0.002
Discrete vs. Linear models				−0.058	0.148	−0.090			
Censored vs. Linear models				−0.069**	0.224**	−0.125			
Censored vs. Discrete models				−0.041	0.076	−0.035			
Journals	−0.136	−0.049	0.184	0.114	0.136	−0.259**	0.076	−0.026	−0.051
Sample size (ln)	−0.028	0.017	0.011	0.041	−0.019	−0.022	0.021	−0.040	0.019
Publication year	0.033	−0.052	0.019	−0.008	0.012	−0.004	0.018	−0.000	−0.018
Pr(y = j)	0.400	0.353	0.247	0.159	0.532	0.310	0.202	0.685	0.113

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; [a]+1 for the factor variables and +SD (standard deviation) for sample size and publication year; standard errors are not reported; moderator variables that have <20 observations (Supplementary Table 10) are excluded (Wehkamp et al., 2018).

However, we observed few changes in the predicted probabilities of different age and household size effects depending on the primary studies' survey design and sample size. For example, studies with multiple-round surveys had a higher likelihood of finding a negative household size effect and a lower likelihood of finding a statistically insignificant age effect. Similarly, studies with larger

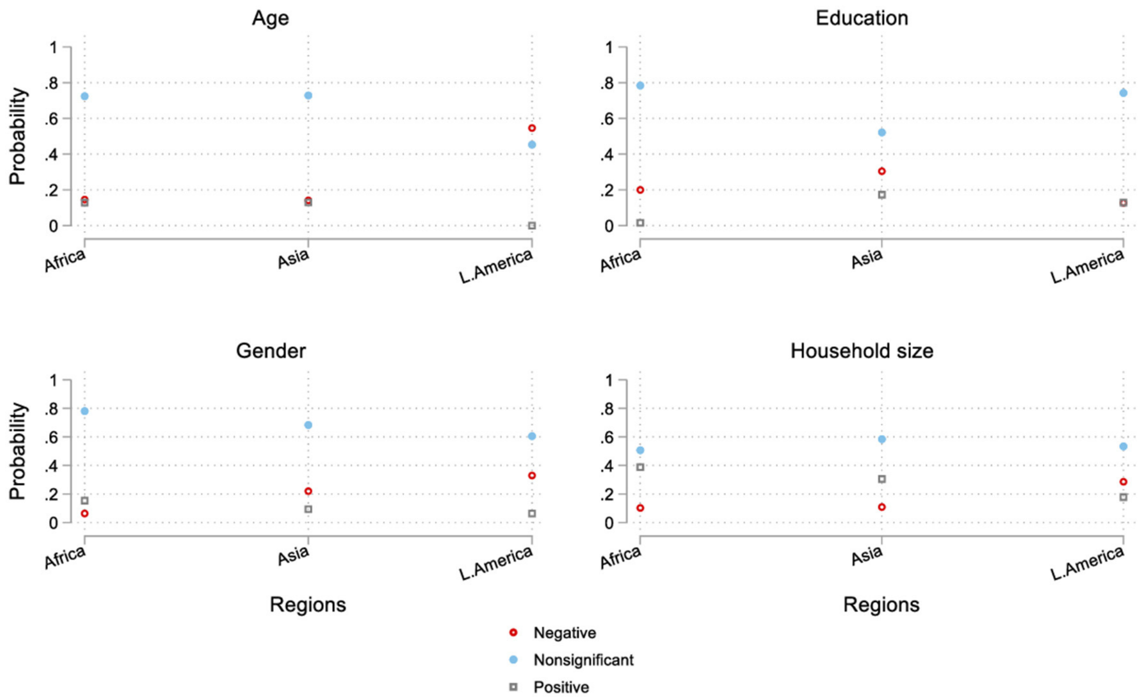

FIGURE 5
The average probability value in Africa, Asia, and Latin America for the age, education, gender, household size covariates.

sample sizes had a higher probability of finding a positive age effect and a lower probability of finding an insignificant one. Moreover, including age-squared in the regression in the primary studies increased the probability of finding a positive age effect, suggesting that older household heads may depend more on environmental resources in the study areas. However, the age-squared coefficients were mostly positive but statistically insignificant in the primary studies. We also found that the effect of age on environmental reliance was significantly stronger than that on environmental income (Table 5).

3.2.4 Publication bias

Table 6 presents the publication bias test results. The F-test is significant at <0.01 significance level for all cases (thus rejecting the null hypothesis). This indicates that studies based on small sample sizes with significant effect estimates were published more frequently than studies based on a large sample size with statistically insignificant estimates.

TABLE 6 Publication bias regression result of the absolute ln (t-value) against ln (sample size).

Variables	All sample	Income sub-group[a]
Sample size (ln)	0.054*	0.054
	(0.032)	(0.035)
Constant	−0.128	−0.177
	(0.189)	(0.207)
Summary statistics		
Observations	776	574
R-squared	0.0037	0.0041
Adj. R-squared	0.0024	0.0024
F test (Ho: β = 1)	871.76***	720.80***

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; [a]Income sub-group comprises AI and RI.

4 Discussion

The meta-analysis, based on 112 empirical studies conducted in 35 countries surveying more than 52 thousand households and published from 1996 to 2021, provides important insights into household-level reliance on environmental resources and the effect of socioeconomic and geographic covariates on environmental income and reliance.

4.1 Does it matter? The level of household reliance on environment, forest, and NTFP income

The meta-analysis confirms the importance of environmental income in supporting the livelihood of rural households in the Global South. The forest and NTFP income share in total household income were approximately 27%, and the share of environment income was 25%. These results are comparable to the estimates of Angelsen et al. (2014), which are 28% for environmental income and 22% for forest income. The unexpected findings that forest and

NTFP incomes are similar and higher than environmental income are due to regional variations in environmental reliance, sample size variations across studies, and differences in study objectives (degree of focus on forest products). First, regional categorical variables significantly determine the average relative environmental income variation. On average, reliance on environmental resources is higher in Africa compared to Latin America and Asia. Second, our analysis, as also found by Vedeld et al. (2004), showed a probability of overestimating forest reliance due to case studies biased toward surveying high forest-reliant households. Specifically, we found that studies based on a small sample reported a higher mean relative environmental income, an effect even more pronounced for NTFP and forest income.

It should also be noted, however, that some studies may under-report environmental income due to households' reluctance to disclose income from illegal product harvesting, such as timber (Asfaw et al., 2013). Studies that revealed income from illegal activities reported a higher share of environmental income. For instance, in a study by Makoudjou et al. (2017), households' relative forest income doubled when income from illegal logging was reported. In another study, the illegal forest income increased the relative forest income by 166% (Mohammad Abdullah et al., 2016).

Many studies also exclude income from environmental services, as these may be difficult to quantify (Vedeld et al., 2007), leading to an underestimation of absolute household incomes and possibly a distortion of relative incomes. This points to a need to apply broader frameworks (Díaz et al., 2018; Miller and Hajjar, 2020) that incorporate non-material and regulating contributions of environmental resources to households' livelihoods and wellbeing. There is a growing body of literature using environmental valuation techniques (e.g., hedonic prices) to quantify environmental services and these could be reviewed to add to the present findings on the values of environmental products.

4.2 What matters? The effect of covariates on environmental income and reliance

We analyzed the effect of covariates (age, education, gender, household size, and distance from environmental resource sites) on environmental income and reliance. On average, young, male-headed, with less or no education, households with more family members, and living near resource sites rely more on environmental products and earn a higher amount of environmental income. However, disaggregation between AI and RI provides a more nuanced picture of the effect of covariates. The regional categorical variables were important in explaining variation, but the methodological variables were not. For example, multiple survey frequencies did not increase the probability of statistically significant effects. Hypothetically, a quarterly household survey improves the accuracy of data collection, especially income data (Angelsen et al., 2011). We also assumed that a large sample size increases the precision of the covariates' effect. However, studies based on a large sample size did not improve the probability of finding significant negative or positive effects.

4.2.1 Distance to the resource sites

For distance, the proportion of positive and negative effects was higher than the nonsignificant effect. More importantly, the average predicted probability of distance's positive and negative effect on absolute income was significantly higher. The positive significant effect implies that households living far from the resource site earn a higher environmental income, even as their reliance is lower. Nguyen et al. (2018) argued that households who travel longer distances extract more valuable environmental products like timber that increase their (cash) income to justify the higher opportunity cost of time and effort (see also Angelsen et al., 2014). Households living near the resource sites extract more environmental products primarily for subsistence (Charlery et al., 2016; McElwee, 2008). As households integrate into the market, they extract more valuable environmental products (Belcher and Ruiz-pérez, 2001). Expanding infrastructure like roads may increase absolute income for households near environmental resources (Charlery et al., 2016). However, there is a risk of overexploitation, especially without appropriate institutional arrangements.

4.2.2 Age

Our analysis of the primary studies reveals that the negative age effect is more prevalent, meaning that younger households tend to earn and depend more on environmental income than older ones. However, as the household age increases, the likelihood of a positive effect on environmental reliance also increases relative to absolute environmental income, while the negative effect decreases. This pattern varies by region, with Latin American studies reporting more negative age effects than Asian and African ones. Many studies that found a significant negative age effect attribute it to the labor-intensive and time-consuming nature of environmental resource extraction, which favors young household heads who can engage in physically demanding high-return environmental resource activities (e.g., Angelsen et al., 2014; Dash et al., 2016; Ezebilo and Mattsson, 2010; Fonta and Ayuk, 2013; Garekae et al., 2017; Gunatilake, 1998; Lepetu et al., 2009; Mamo et al., 2007; Melaku et al., 2014; Rayamajhi et al., 2012; Suleiman et al., 2017; Thondhlana and Muchapondwa, 2014; Uberhuaga et al., 2012; Wei et al., 2016). For example, Thondhlana and Muchapondwa (2014) observed that in the Kalahari drylands of South Africa, where trees, shrubs, and herbs are spatially distributed, the youth with physical strength travel longer distances to collect fuelwood and culturally valuable crafts, bush meats, and medicinal plants.

In addition to physical strength, other studies associated the negative effect of age on environmental income and reliance with risk. In some areas, such as the Nyungwe Forest Reserve of Rwanda (Masozera and Alavalapati, 2004) and the Falgore Game Reserve of Nigeria (Suleiman et al., 2017), the authorities restrict or prohibit forest product extraction. Nevertheless, younger households are more willing to take risks and break the rules to access forest products. Another factor that influences environmental income and dependence is that older households have more assets and alternative sources of livelihood, such as crops and livestock (Angelsen et al., 2014; Yego et al., 2021).

The negative effect of age on environmental income and reliance has two crucial implications. First, while much of forest land in the Global South is owned and managed by the state, it may often constitute de facto open-access resources. A large proportion of the rural population is young in Africa and Asia, and such households may want to access environmental resources, which puts pressure on sustainable management. This is further exacerbated by high unemployment and poverty among the rural youth who have limited access to agricultural lands and less opportunity for off-farm activities (Ezebilo and Mattsson, 2010; Garekae et al., 2017; McElwee, 2008; McSweeney, 2004). This indicates a need to promote education and vocational training as educated households rely less on environmental products through more opportunities to diversify their livelihood (Adhikari, 2005; Ezebilo and Mattsson, 2010; Suleiman et al., 2017). Besides, creating opportunities for the youth in urban and peri-urban areas to engage in off-farm activities would help them send remittances that reduce reliance on environmental products.

Second, as the extraction and sale of environmental products provide income to young households (McSweeney, 2004), interventions that facilitate access to and management of environmental resources (Humphries et al., 2020) can help such households to either "step up" and specialize in the production of these products sustainably or to "step out," creating capital and building assets to diversify into other livelihood sources (Furo et al., 2022; Miller and Hajjar, 2020). However, there is limited empirical evidence documenting the role of forests and non-forest environmental resources as a pathway out of poverty (Waleligne et al., 2019).

4.2.3 Gender

In our meta-analysis, the proportion of the negative effect of gender on environmental income and reliance is much higher, indicating that female-headed households earn less absolute environmental income and rely less on environmental resources than their male counterparts. However, the average probability of a positive gender effect on environmental reliance increases, and that of a negative effect decreases with reference to the absolute environmental income, which indicates that the proportion of female-headed households earning a higher absolute environmental income is much lower than the proportion of them depending on environmental resources. The primary studies found that women collect environmental products primarily for subsistence, whereas men travel longer distances and engage in riskier and labor-demanding activities to extract high-value environmental products mainly for sale (Adhikari, 2005; Asfaw et al., 2013; Thondhlana et al., 2012). This finding aligns with a global comparative study where men specialized in extracting forest products for cash income (Sunderland et al., 2014).

Our meta-analysis further shows that the average probability of finding a significant negative gender effect on environmental reliance is higher in Asia and Latin America than in Africa. Women extract unprocessed environmental products with a higher share of the total income than those collected by men in Africa. In contrast, men dominate the extraction of almost all processed and unprocessed environmental products in Latin America (Sunderland et al., 2014). However, there are also situations where environmental resources are vital for female-headed households (e.g., Adongo et al., 2019; Ali and Rahut, 2018; Asfaw et al., 2013; Babulo et al., 2008; Baiyegunhi et al., 2016; Beyene et al., 2020; Uberhuaga et al., 2012). For instance, where land ownership and access to other capitals are limited, women may pursue higher forest reliance (Asfaw et al., 2013).

The relationship between gender and environmental income and reliance is also mediated by gender-roles and formal and informal institutional constraints. In many locations, environmental resource extraction decision-making and leadership are mainly associated with older male adults (Adhikari, 2005; Luna et al., 2020). Due to cultural norms, in some places, women are not allowed to enter forests (Suleiman et al., 2017), engage in the collection of forest products for sale (Yego et al., 2021), or their area of operation is limited due to home responsibilities (Adhikari, 2005; Thondhlana et al., 2012). Confined to nearby environmental resource sites, they often participate in the collection of low-value environmental products (Dash et al., 2016), mainly for subsistence purposes.

The above findings from the primary studies are widely corroborated in the literature. In a study of marginalized peoples' natural resource governance, Colfer (2011) found that formal institutions in countries like India, Burkina Faso, and Zimbabwe sometimes deem women's resource extraction illegal. In their global comparative study, Sunderland et al. (2014) found that women participate far less than men in formal forest user groups, often not attending meetings. In a recent systematic review, Duguma et al. (2022) further questioned the genuineness of women's participation in the sustainable management of forests in Africa. Agarwal (2009) also emphasized the need to empower women in decision-making roles, which also serves to increase the pool of people committed to environmental resource conservation. For example, forest user groups in Nepal and India with more women on the executive committee tended to be associated with better forest conditions (Agarwal, 2009).

4.2.4 Education

The meta-analysis of the primary studies revealed, on average, a negative association between education and environmental income and reliance. Households with higher education levels tend to rely less on environmental income, as education enables them to access more lucrative employment opportunities in alternative livelihood strategies (Wei et al., 2017). Baiyegunhi et al. (2016) demonstrated that the opportunity cost of harvesting mopane worms increased as the educational status of households changed, particularly among young women. Education facilitates the acquisition of new information, skills, and knowledge that enhance people's awareness, exposure, and employability in the job market. Consequently, people can migrate and secure jobs in urban areas and other sectors of the off-farm labor market, such as civil service and non-governmental organizations (Angelsen et al., 2014; Kimengsi et al., 2020). Moreover, better-educated households are more likely to adopt improved agricultural production techniques to increase their income (Tufail et al., 2021). Education is expected to increase the earning potential, diversify employment opportunities, improve the geographical mobility of labor, and provide higher and more reliable sources of non-farm income opportunities, which often also enhance households' asset base and welfare (Ali et al., 2020; Kamanga et al., 2009). These education benefits demonstrate the importance of investing in human capital in rural communities (Jiao et al., 2019).

The effect of education on environmental reliance varied across regions, with Latin America showing a lower probability of a negative and significant association. Conversely, more studies in Asia found a positive association between education and environmental reliance than in Africa. The higher education enrollment rates in Asia and Latin America could partly explain this. However, other mechanisms may also be found. Gunatilake (1998) showed that the link between education and wages is weakened when there is a surplus of educated but unemployed people. Ali and Rahut (2018) suggested that households with educated heads may collect more environmental products because they are more aware of the types, values, and market opportunities of these products than those with no education. Supporting this view, Dash et al. (2016) reported that more educated people engaged in collecting valuable medicinal herbs that generate higher cash income. Educated people also had better access to new information on sustainable harvesting, resource use, and management and a better ability to process and benefit from the resources (Baiyegunhi et al., 2016; Tufail et al., 2021). Moreover, due to limited access to land and public sector jobs, young and educated households may specialize in high-value products. This implies that expanding access to education in rural areas, especially in Africa where enrollment is low, creates the opportunity for young men and women to diversify their livelihood strategies and reduce environmental income reliance or raise awareness of people who could use environmental resources sustainably.

4.2.5 Household size

Our meta-analysis revealed a higher likelihood of a positive effect of household size on environmental income and reliance, suggesting that, on average, larger households depend more on environmental resources for their livelihoods. Several primary studies in our review argued that households with many members have "more mouths" to feed and have "more hands" to collect various environmental products (e.g., Adongo et al., 2019; Hussain et al., 2019; Kar and Jacobson, 2012). In most scenarios, a large household size with limited access to alternative income sources may outweigh any economies of scale in consumption reduction, resulting in higher per capita extraction of environmental products. Since environmental resource extraction requires intensive labor and time, larger households would have more people to allocate to different collection and gathering activities and thus obtain more resources from the environment (Ali et al., 2020; Bierkamp et al., 2021; Mahdavi et al., 2019). However, we observed a significant regional variation. The average probability of reporting a negative household size on environmental reliance was higher in Asia and Latin America than in Africa. This may reflect a higher worker-consumer ratio where adult labor in the household may diversify their economic activities to rural wage employment, self-employment, and other activities that reduce labor input in extractive activities, leaving only children to participate (Uberhuaga et al., 2012).

A common challenge in large households is the low per capita availability of land, which results in disguised unemployment and underemployment in the agricultural sector. Because of the lack of alternative income opportunities in the off-farm sector, many households rely on environmental resource extraction (Masozera and Alavalapati, 2004; Sathyapalan, 2005). For instance, Babulo et al. (2008) reported that the average land holding among sample households in Northern Ethiopian highlands was about one hectare per household, with an average household size of six, leading to underemployment of some household members. Moreover, Li et al. (2021) argued that larger household sizes reduced the likelihood of farmers improving their total income and building their assets and increased the likelihood of becoming income- and asset-poor. This implies that households with more members have lower asset accumulation, which may lead to higher pressure on environmental resources and unsustainable management.

4.3 Limitation of the meta-analysis

The following limitations of our meta-analysis should be considered while interpreting the results. Firstly, we adopted the definition of environmental income as income from uncultivated natural resources (Sjaastad et al., 2005). However, there is no common application of an agreed-upon income definition across the studied papers. The same is true for the terms forest and non-timber forest product. This means that income has not been consistently reported in the same way in the primary studies. Secondly, we confine our meta-analysis to published articles. The meta-analysis revealed the existence of publication bias. Hence, we suggest that future meta-analyses also incorporate unpublished studies, acknowledging that the quality of unpublished studies would need to be assessed. Thirdly, our meta-analysis partially explains the covariates' effect on environmental income and reliance based on a directional effect. Although the directional effect has policy implications *per se*, future meta-analyses should also aim to estimate the effect size of each covariate as more methodologically relatively homogeneous empirical studies become available.

The issue of risks of bias also warrants further attention. Noting that there is no established strategy to assess risks of bias in observational studies (Page et al., 2021), we assessed potential biases by incorporating moderator variables (sample size, journal types, and survey frequency) into our models. Three findings were notable. First, studies with smaller sample sizes tended to estimate higher levels of environmental reliance, suggesting that studies focusing on forest-dependent households may introduce selection bias. Second, using the approach of Card and Krueger (1995), we found that studies with smaller sample sizes and significant effect estimates were published more frequently than those with larger sample sizes and insignificant effects, suggesting a potential publication bias. Third, we did not find consistent evidence that studies measuring environmental income in multiple rounds were different from those using a single measurement point (and thus longer recall periods). Although our robustness checks showed consistent and comparable results, the potential underlying biases necessitate cautious interpretation of the results.

5 Conclusion and recommendations

Our meta-analysis is based on a global analysis of 112 studies and provides three important insights. First, the expanded body of literature published in the last decade supports the findings of Angelsen et al. (2014) on the relative economic importance of environmental income to rural households in the Global South: such income matters. The reviewed empirical studies reported an average environmental reliance of 25.3 ± 10.5%. Second, we found sample size and regional categorical variables to influence the variation in environmental reliance significantly. A negative relationship existed between sample size and environmental reliance. Studies were also biased toward forest products. Moreover, the relative environmental income is lower in Asia and Latin America than in Africa. Previously, Angelsen et al. (2014) reported the highest reliance in Latin America. Third, we quantitatively examined the effect of covariates on environmental income and reliance and found most effect estimates to be non-significant. The effect of distance on environmental income was the only case where the predicted probability of the non-significant category was lower than the negative and positive effect categories. This indicates a need to pay more attention to distance in the design of future studies. However, irrespective of the significance level, on average, young, male-headed households with less or no education, many family members, and living near resource sites rely more on environmental products and earn a higher environmental income.

Based on these results, we propose the following recommendations. First, future studies on environmental income and reliance should move beyond the forest to include non-forest environmental products. Such initiatives should also strive to build trust with households to gather income information on environmental products whose harvest authorities view as "illegal." Second, researchers should check the robustness of covariates. Reporting these findings should be required in connection with publication. Third, on average, young household heads earn more absolute environmental income and rely more on environmental resources due to their physical ability, time availability, and risk-taking tendencies. Conversely, despite the importance of environmental resources for women, female-headed households earn less absolute environmental income and rely less on environmental products primarily due to institutional constraints. Rural policy interventions that aim to reduce poverty and sustainably manage environmental resources such as forests should focus on young households as significant stakeholders. In doing so, it is crucial to identify and involve actors living far from environmental resources as they extract valuable environmental products.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

GS: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing, Data curation, Visualization. CS-H: Conceptualization, Methodology, Supervision, Writing – review & editing, Formal analysis, Validation, Visualization. SW: Conceptualization, Methodology, Supervision, Writing – review & editing, Formal analysis, Validation, Visualization.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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