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Tackling the challenges of assessing socioeconomic impacts of farmland restoration: The case of Malawi

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ABSTRACT

This research explores the potential of using the secondary household survey data to identify key socioeconomic indicators for tracking farmland restoration progress in Malawi since 2017. A two-year panel data for the periods between 2016–2017 and 2019–2020 was created for the analysis, building on data collected from Malawi's Integrated Household Panel Survey (IHPS). An initial data analysis shows that estimated average Household Restoration Intensity Score (HRIS) increased from 2.05 in 2016 to 2.24 in 2019, indicating increased intensification of farmland restoration at the household level over time. The average Food Consumption Score (FCS) of all the households also significantly improved over time, rising from 43.19 in 2016 to 47.43 in 2019. A Difference-in-Difference (DiD) model was developed to quantitatively estimate the causal effects of the farmland restoration interventions on the socioeconomic improvement of rural households. Overall, the model shows some promising results. All four regressions generated statistically significant results regarding the positive impact of restoration interventions over time on four socioeconomic indicators, including food and non-food expenditure, crop sales, and FCS at the household level. However, the model results should be interpreted with care due to clear caveats on secondary household survey data. In response, this study recommended three concrete ways that surveys can be improved to collect data that is relevant for assessing the socioeconomic impacts of farmland restoration. This study also calls for urgent global actions to construct a robust restoration monitoring and evaluation system that will allow systemically monitoring and tracking socioeconomic improvements resulting from restoration interventions in a consistent manner over time.

1. Introduction

In 2019, the United Nations established 2021–2030 as the Decade on Ecosystem Restoration (hereafter referred to as the UN Decade) to focus global efforts on preventing catastrophic climate change and reviving ecosystems around the world for the benefit of people and nature. The UN Decade seeks to accelerate existing restoration targets like the Bonn Challenge[1], and as such, significant financial resources will be channeled toward restoration. It is therefore imperative that these restoration investments could directly benefit local communities and improve the livelihoods of the intervening populations. Especially, this is important for smallholder farmers who are the backbone of agriculture in many developing countries. For instance, over 60% of the population of sub-Saharan Africa is smallholder farmers that own less than one hectare

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[1] The Bonn Challenge is a global goal to bring 150 million hectares of degraded and deforested landscapes into restoration by 2020 and 350 million hectares by 2030. Countries and organizations energized by the Bonn Challenge have fostered regional political and technical cooperation spaces to share expertise and lessons learnt. These initiatives include the African Forest Landscape Restoration Initiative (AFR100), Initiative 20x20 in Latin America and the Caribbean, ECCA30 in Europe, Caucasus and Central Asia, and the Agadir Commitment in the Mediterranean region.

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of land (Giller et al., 2021; Goedde et al., 2019).

In the literature, biophysical benefits associated with landscape restoration and ecosystem protection are relatively well-documented. For instance, research has shown that enrichment plantings of trees, shrubs and grasses in agro-silvo-pastoral systems are key to restoring degraded lands and building landscape resilience (Sacande et al., 2021; Berrahmouni et al., 2015; Ellison and Speranza, 2020; Yirdaw et al., 2017). However, socioeconomic research that could quantitatively assess the linkages between restoration interventions and benefits to people remains scarce (Miller et al., 2019). Some studies attempted to establish correlations between tree-cover increases with the improvement of local income (de Jong, 2010), nutritious food intake (Johnson et al., 2013; Rasolofoson et al., 2018), and clean drinking water (Mapulanga and Naito, 2019), but fewer analyses have used socioeconomic data that are directly collected from affected communities *before, during* and *after* the implementation of restoration interventions to examine the extent to which restoration interventions have contributed to livelihood improvement.

The relative scarcity of research on the socioeconomic impacts of restoration is in part due to inadequate resource allocation, and in part due to the complexity involved in socioeconomic analyses, as there is difficulty in isolating restoration from other factors that have influence over socioeconomic outcomes. A lack of robust data, including a lack of consistent data collection methods over time and space and the lack of standardized analytical approaches, are the main hinderances that need to be overcome.

More specifically, there is a lack of commonly agreed methods and socioeconomic indicators for defining the baseline and tracking socioeconomic improvement over time associated with restoration interventions. Although robust socioeconomic indicators and data collection systems (i.e., nationwide household surveys) broadly exist, most of them are not specifically designed to measure and track socioeconomic impacts associated with restoration interventions. Without a clear baseline, the attribution of restoration to socioeconomic improvements of the local rural communities may be obscured by other factors, such as macro-level policy interventions or microcredits that allow rural households to generate greater level of income, consumption, and wealth through investment. Additionally, national survey questionnaires do not capture informal activities on farmlands, which could potentially alter the results obtained in the baseline survey and/or among the control groups (Sacande et al., 2021).

As restoration efforts are expected to scale quickly in the coming years, it becomes more urgent than ever to tackle these data challenges to better inform investment decisions regarding where to prioritize restoration efforts to scale up the socioeconomic impacts (Ding et al., 2017). Although important progress has been made through several global initiatives, including the FAO Framework on Ecosystem Restoration Monitoring (FERM)[2], the Restoration Project Information Sharing Framework (ISF) (Gann et al., 2022), and the Economics of Ecosystem Restoration (TEER)[3] (Bodin et al., 2021), a global architecture that allows systemic collection of standardized socioeconomic data from restoration sites has yet to be developed to address long-term data needs.

Despite these challenges, this paper attempts to seek interim solutions that could help improve our understanding of the socioeconomic impacts of restoration when we are facing data constraints. In particular, this paper aims to advance socioeconomic research on restoration by: (1) developing an analytical framework to analyze the causal relationship between restoration and socioeconomic impact and identifying relevant indicators and data needs for such analyses, and (2) exploring whether and to what extent secondary household survey data sets can be used for assessing socioeconomic impacts of restoration progress in the short term, when primary data collected at restoration project level is still absent.

This study uses farmland restoration in Malawi as a special case to contextualize the analysis due to its historical record of restoration efforts and relatively good data availability[4]. Hence, in the remaining body of the paper, restoration in Malawi is mostly referred to as farmland restoration. Malawi has suffered severe land degradation and lost revenue over the past several decades. It is estimated that between 2001 and 2009, land degradation cost Malawi an estimated $244 million per year (6.8 % of GDP) (Kirui, 2015). Poor farming practices that degrade croplands for maize, rice, and wheat resulted in a loss of $5.7 million per year (Kirui, 2015). To counter land degradation, the government turned to forest and landscape restoration as a strategy to help economic development, reduce poverty, increase food security, and build climate resilience (Republic of Malawi, 2017). In 2017, the country pledged to bring a total of 4.5 million hectares of degraded and deforested land under restoration as a contribution to AFR100, of which about 2 million hectares is agricultural land (Republic of Malawi, 2017). Since then, Malawi's economy has seen significant improvement, with its GDP world ranking moving from 146th in 2017 (Worldometers, 2017) to 141st in 2021 (Countryeconomy, 2021). Therefore, the most intriguing question that this research will address is whether implementing restoration has contributed to the observable socioeconomic growth in the past years.

The remaining paper is organized as follows: section 2 discusses the methodological framework and socioeconomic data sets that are used to identify most relevant socioeconomic indicators for assessing causal relationship between restoration interventions on farmland and social economic impacts. An econometric model is developed to examine whether the selected socioeconomic indicators are appropriate for assessing the impacts of restoration progress. Section 3 discusses the model results. Section 4 concludes the research and highlights the future research needs.

2. Research setting and methodology

2.1. Linking restoration interventions to its impacts: A methodological framework

2.1.1. The causal links between restoration interventions and socioeconomic impacts

Restoration interventions on farmland in Malawi refer to a wide range of regenerative agricultural practices, including conservation agriculture (CA), farmer-managed natural regeneration (FMNR) and agroforestry (Republic of Malawi, 2017). CA is a type of agricultural technique that minimizes tillage and soil disturbance and involves permanent soil cover (such as with crop residue or live mulch) and crop rotation or intercropping (Republic of Malawi, 2017). FMNR is a specific type of agricultural technique in which farmers do not plant trees but rather manage and cultivate the natural regrowth of trees on their farms instead of eliminating them (Republic of Malawi, 2017). FMNR uses leguminous- or nitrogen fixing-trees to enhance the productivity of agricultural land. Agroforestry refers to a broad array of techniques that involve tree planting on cropland to stabilize the soil and improve soil fertility. All of these activities help to boost crop yields and increase food security, with the added benefits of providing fodder for grazing animals.

The choices and adoption of restoration interventions in different locations depend largely on three main factors: (1) types of crops, (2) topographic and climatic conditions, and (3) socioeconomic

[2] https://ferm.fao.org/

[3] https://www.fao.org/in-action/forest-landscape-restoration-mechanism/our-work/gl/teer/en/

[4] Malawi has a long history of receiving foreign aid, both monetary and technical support, for its health and other services provision, including completion of socioeconomic household surveys. As a result, the country has relatively good database for conducting a quantitative impact assessment.

characteristics of the local communities (such as income, land tenure, education, gender, demography, religion, etc.). The first two together determine what restoration interventions are most suitable for the farmland in question, whereas the latter influence whether and how fast restoration interventions can be adopted by local communities and/or farm households.

As far as socioeconomic impacts are concerned, there are at least two tiers of impacts that have been identified in the literature. First, land restoration interventions improve biophysical soil conditions, which can lead to increased crop production, directly benefiting landowners in terms of food security, income generated from surplus crops, timber and non-timber forest products, and/or direct cash payments by restoration projects. These benefits refer to the *first-tier socioeconomic impacts* of the specific restoration interventions.

For instance, Fungo et al. (2016) found that in rural forest-dependent households in Cameroon, forest foods contribute 93% of women's vitamin A intake, 100% of sodium, 85% of iron, 88% of zinc, and 89% of calcium. These findings suggest that tree-based restoration interventions in areas that are ecologically suitable for trees can play a significant role in food security for local communities. Moreover, researchers also found that income is significantly correlated with tree cover in some areas. Angelsen et al. (2014) studied 24 developing countries and found that forest products contribute 22% of the total income of rural households. Restoration can also improve farmers' incomes by creating on-farm employment opportunities or providing government subsidies or fiscal transfers, such as Payment for Ecosystem Services (PES), which are cash payments that governments make to farmers if they stop engaging in unsustainable farming practices and land conversion or if they implement sustainable and restoration practices (Adams et al., 2016). Additionally, increased soil water retention could improve both the quality and support of drinkable water to local communities.

Furthermore, extra income generated from restoration projects can lead to the *second-tier socioeconomic impacts*, which are more indirect. For instance, increased drinkable water and income can help individual farmers and households strengthen their social resilience to climate change and reduce poverty. In some cases, cash gains from the sales of agricultural and timber products can also be used for buying additional food resources, which in turn further strengthens households' food security. At the community level, part of the revenues generated from restoration projects can be reinvested in local schools and health care systems, which are important investments in human capital to ensure future economic prosperity of the community. Continuous investment in human capital can have amplified long-term impacts on local communities including improved gender equity and land tenure security, etc.

Similarly, Miller et al. (2020) conducted a panel data analysis in Uganda and found that growing trees on farms, especially fruit trees, has significantly improved household well-being in terms of increased income, food security, and nutrition. Trees on farms were associated with increased consumption of food directly produced by households or bought using cash income generated from selling tree products. Additionally, extra income can improve local livelihoods by providing additional sources of food, inputs for agriculture production, tuition fees, or health care. However, due to the scattered empirical analyses in the literature, the evidence of a positive or negative correlation between the well-being indicators and restoration intervention is not well-established.

These causal links between farmland restoration interventions and socioeconomic impacts are captured in Fig. 1. The next step is therefore to select the most relevant indicators for measuring farmland restoration interventions and socioeconomic impacts, as well as data to quantitatively examine this causality.

2.1.2. Data description

In the literature, evaluating the socioeconomic impacts has mostly relied on data generated from household surveys, which are currently the most important data source for a range of key demographic and socioeconomic statistics for developing countries in which vital registration and administrative systems are lacking and the information gaps are largest. This study relies on Malawi's Integrated Household Panel Survey (IHPS), a longitudinal survey conducted in four waves:

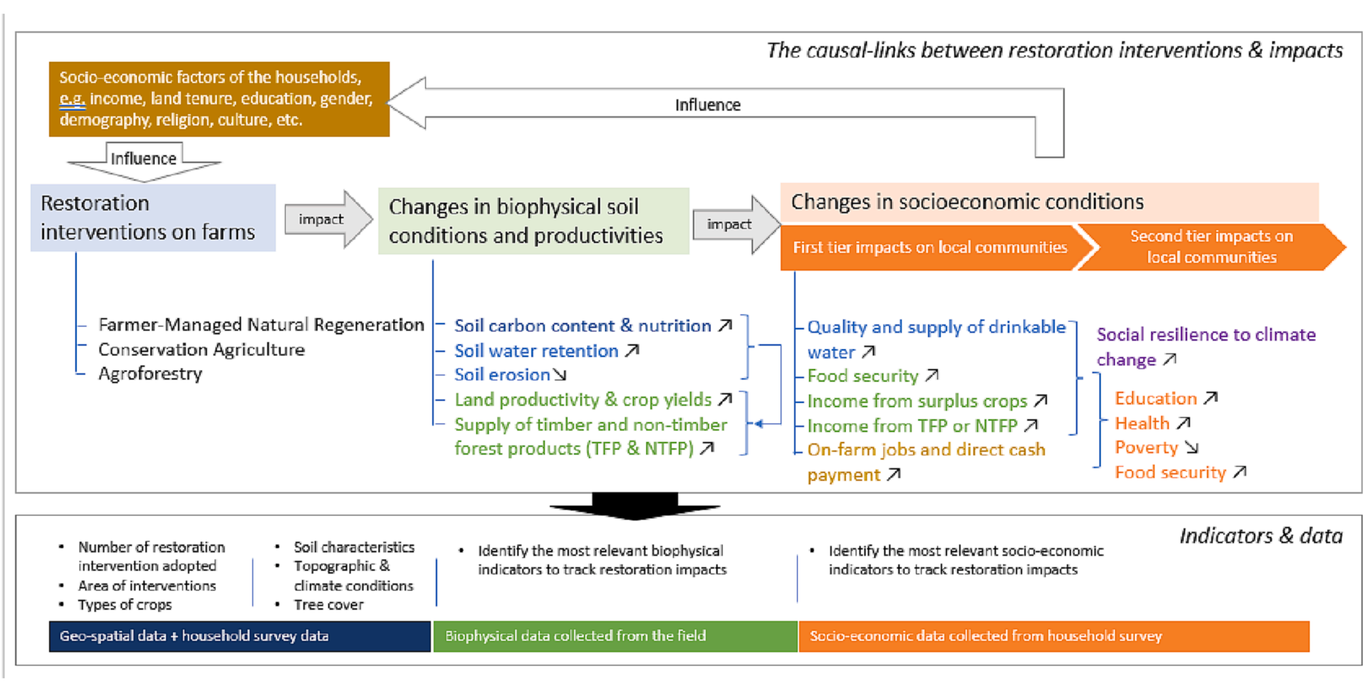

Fig. 1. The analytical framework for assessing causal-links between restoration and socioeconomic impacts (Note: Food security refers to a situation where "all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (World Food Summit, 1996). Hence, it can be treated as either first-tier or second-tier impact. Food security is a first-tier impact of restoration when it is achieved directly through increased agricultural output or forest foods on restored agricultural land or forests. It is treated as a second-tier impact when food security, including quantity and variety of food, is achieved through income improvement that are attributed to restoration activities.)

2010–2011, 2013–2014, 2016–2017, and 2019–2020. The surveys, implemented by Malawi's National Statistical Office (NSO) and supported by the World Bank's Living Standards Measurement Survey (LSMS), study trends in poverty, agriculture, and socioeconomic characteristics across a standard panel of households. Crucially, they are designed to be representative at the national level and across urban and rural areas in mainland Malawi. This IHPS design allowed us to analyze the connections between farmland restoration and socioeconomic outcomes at the level of individual households.

Our study was conducted using the 2016–2017 (hereafter referred to as 2016) and the 2019–2020 (hereafter referred to as 2019) waves, allowing us to focus on potential shifts in adoption of farmland restoration interventions following the 2017 national pledge. The 2016 IHPS collected data from 2,508 households across 102 enumeration areas (EAs). These included 1,908 households from the 2013 survey, along with 600 additional households formed by individuals splitting off and forming their own or joining other households, which were then included in the survey. Approximately 81% of the 2016 sample were rural households; about 4 % lived in the northern region of the country, 45% in the central region, and 50% in the south. In 2019, the survey collected data from 3,178 households across 102 EAs (Fig. 2), 2,368 of which came directly from the 2016 sample. Our survey focused on a sample of 1,522 rural households across Malawi that had full data availability for all variables for both 2016 and 2019.

2.1.3. *Indicators of restoration intervention*

Large-scale land restoration is typically monitored via satellite imagery or other remotely sensed spatial data that can detect changes in tree cover, land cover, and other biophysical indicators. However, for this study, we were unable to rely on such data to locate and/or validate restoration interventions on farms because the IHPS survey does not disclose the geographic coordinates of individual households and farms to protect the privacy of the respondents. Instead, we relied on responses to questions in the IHPS agriculture questionnaire to identify households that had implemented conservation agricultural practices to restore degraded farmlands. Five types of farmland restoration interventions are included in this analysis, i.e., (i) soil and water control, (ii) cover crops, (iii) crop residue treatment, (iv) minimum and zero tillage agriculture, and (v) intercropping and mixed stands (Amadu et al., 2021; Ayele et al., 2018; Douxchamps et al., 2015).

Data on farmland restoration interventions were collected at the level of individual plots of land. In contrast, the socioeconomic data were collected at the household level. However, questions about farmland restoration interventions in the questionnaire only require binary types of answers, i.e., Yes = 1 or No = 0 (See Appendix 1 for details), which does not reveal any information about the extent of restoration on each plot, nor the effectiveness associated with individual interventions. Furthermore, one household might own multiple plots of land, and more than one intervention type might have been applied on each plot.

To cope with poor data quality as well as the mismatches in the data collection scale and approach, we constructed the household restoration intensity score (HRIS). HRIS is a metric intended to capture the extent of restoration on each plot (given the fact that a variable number and combination of interventions may have been applied on each plot) and to aggregate that to the household level in a way that represents the overall extent of restoration for each household. The HRIS values of our dataset ranged from 0 to 8, with higher scores serving as a proxy for more intense restoration. In other words, HRIS rewards applying more types of farmland restoration intervention to land and applying these interventions across a greater percentage of a farmer's land, without penalizing households with less land.

Eq (1) shows how the HRIS is calculated. For each plot belonging to a single household, we counted the number of interventions applied (out of a maximum total of five). The number of interventions applied on that plot was multiplied by the ratio between the size of the plot and the total land area owned by that household. These two steps are intended to consider both the number of agricultural restoration practices applied on each plot and the percentage of a farmer's land over which these practices were applied. The HRIS is then calculated by summing the restoration intensity scores of all plots owned by that household.

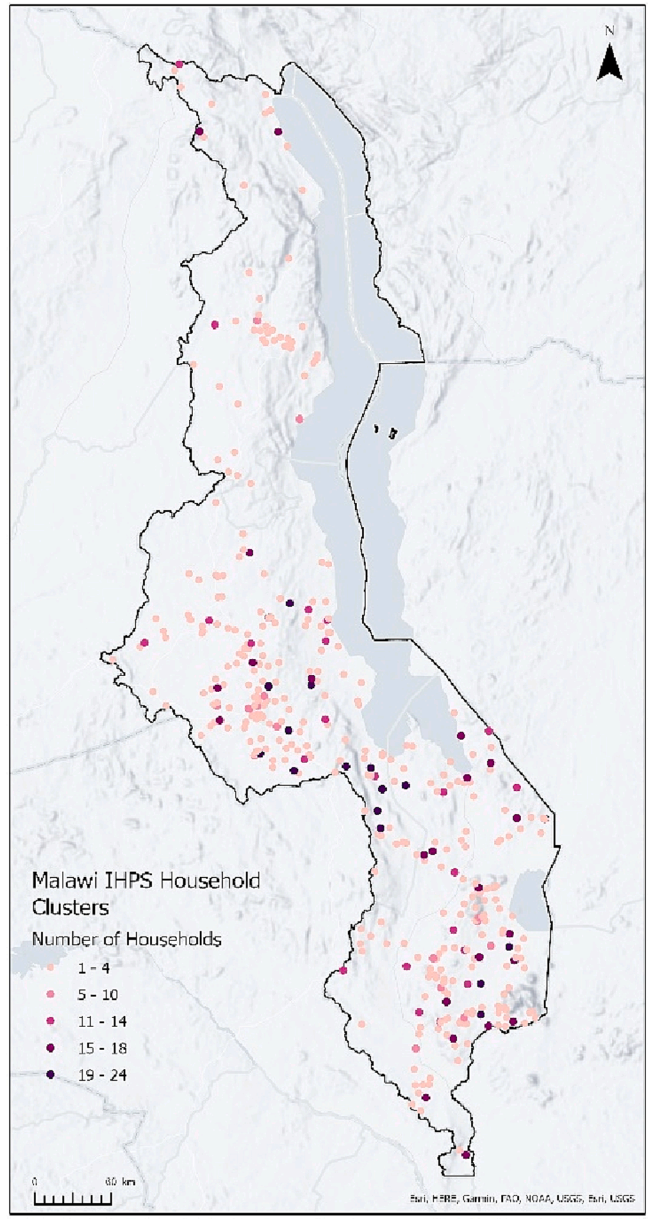

Fig. 2. Spatial distribution of the publicly available coordinates of the household clusters of the 3,178 households in the 2019 survey. (Note: To protect privacy, the individual household coordinates are not given; rather the average coordinates of each EA, offset randomly by 0–5 km, are used.).

$$HRIS = \sum_{i=1}^{n} \left(R_i \times \frac{PA_i}{HA} \right) \tag{1}$$

where n is the number of plots belonging to a single household, i = the index number of each plot belonging to that household, R_i = the number of farmland restoration intervention types applied to plot i (with a maximum of 5), PA_i = the area of plot i, and HA is the total land area of all the plots owned by that household.

Fig. 3 shows that estimated average HRIS score increased from 2.05 in 2016 to 2.24 in 2019. This change is statistically significant (t = 3.56, p = 0.0004), indicating average intensification of farmland restoration at the household level over time. However, the spatial distributions of

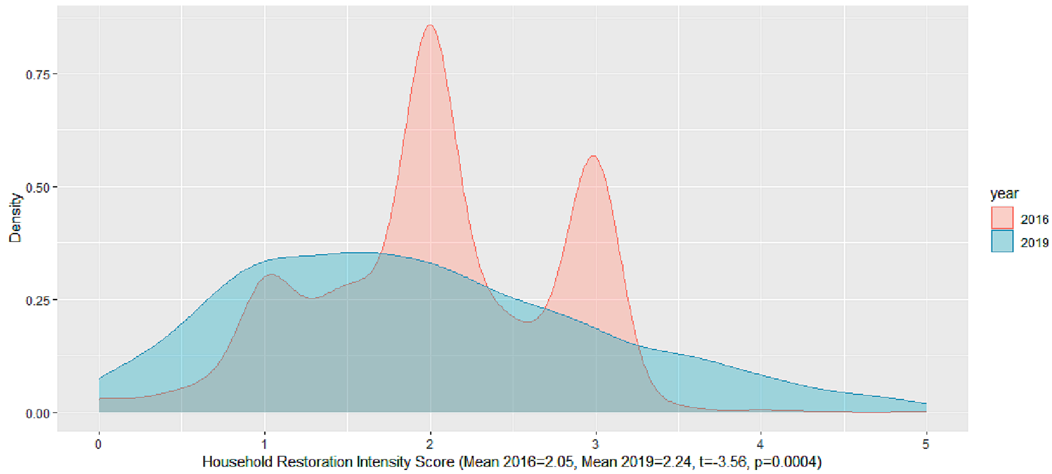

Fig. 3. Distributions of the household restoration intensity scores for 2016 and 2019.

the HRIS in 2016 and 2019 (as shown in Fig. 4) suggested that farmland restoration intensification efforts were unevenly distributed across the country. While the country contains areas of both gain and loss in HRIS, the overall change was an increase in restoration intensity at the household level.

However, one limitation of this methodology is that it assumes all types of interventions generate the same positive effects on the restored farmland, which, on the contrary, can vary widely depending on topographic and climatic conditions, type of restoration activity that was chosen and implemented, as well as the effectiveness of implementation (Ayele et al., 2018; Douxchamps et al., 2015; Ladoni et al., 2015).

2.1.4. Socioeconomic indicators for measuring household wellbeing affected by restoration

Socioeconomic data is often monitored via household surveys such as the IHPS, which have a standardized approach to monitoring socioeconomic development. As discussed earlier, restoration interventions can improve the biophysical conditions of the land, which can have *first-tier* (direct) or *second-tier* (indirect) socioeconomic impacts. In this study, we assume that farmland restoration interventions will improve crop yields (i.e., a biophysical impact), which directly contributes to increased household income (a *first-tier* socioeconomic impact). Subsequently, we assume that higher household income will contribute to increased food security (i.e., a *second-tier* socioeconomic impact), since greater purchasing power enables access to an increased quantity and variety of foods. Based on the existing research and data availability in the IHPS survey, this study utilized two sets of indicators (1) household income to measure the *first-tier* socioeconomic impacts of land restoration interventions in Malawi; and (2) household food consumption, as a proxy for food security, to measure the *second-tier* socioeconomic impacts.

First, household incomes are measured using three sub-indicators, including household non-food expenditure per capita, household food expenditure per capita, and crop sales per capita (Appendix 2). These indicators can be tracked and measured using information on food and non-food household consumption and the sales of harvested crops provided by the surveys. More specially, the household non-food expenditure per capita reflects a household's consumption of durable and non-durable goods in the past 12 months, and the household food expenditure per capita shows a household's food consumption over the past week. Moreover, the crop sales per capita include the sales of both food and cash crops over the rainy and dry season. Fig. 5 shows the normal distribution of the three variables equivalent to 2016 constant price (the data has been logged). The household expenditure decreased, while the crop sales increased across the two survey waves in all the groups of households.

Second, the household food security in Malawi was measured by Food Consumption Score (FCS) (EFSA, 2009). The FCS considers the diversity and frequency of nutrition intake from nine food groups at household level in a period of seven days, which is supposed to reflect both the quantity and quality of food consumed by households. The nine food groups include cereals and tubers, pulses (incl. beans, lentils, and peas), vegetables, fruits, meat and fish, milk, sugar, oil, and condiments. The score is calculated using Eq. (2),

$$\mathrm{FCS} = \sum_{1}^{n} w_n * f_n \; (\mathrm{n} = 1, 2, 3, \cdots, 9) \tag{2}$$

where FCS is Food Consumption Score, w is the weighted value of different food groups. The weighted value is determined based on the nutritional value of different food groups. For example, meat and fish are given a high weight of 4 due to their high nutrition density, while sugar is given a low weight of 0.5 due to its absence of micronutrients and relatively small quantities of consumption in the diet (Appendix 3). f is the consumption frequency of different food groups (number of days in which a household consumed each food group in the past seven days). n represents different food groups.

FCS falls in three categories: poor food consumption (FCS $<$ 21), borderline food consumption (21.5 $<$ FCS $\leq$ 35), acceptable food consumption (FCS $>$ 35). In general, the higher the FCS is, the better status of food security is the household in. However, FCS does not consider food consumed outside of the household nor the quantity of food consumed within the household, and it does not measure long-term food security. Despite this, FCS is still a useful indicator to measure household food security (Mango et al., 2018). Fig. 6 shows that the FCS increased in 2019 compared with 2016. The average FCS of all the households was 43.19 in 2016, and it increased to 47.43 in 2019. The difference over years is statistically significant (t-test = -6.76, p-value = 1.658e-11). The spatial distributions of FCS in 2016 and 2019 are presented in Fig. 7. Like HRIS, FCS also shows an uneven distribution pattern across the country, but a comparison of FCS between two years suggests that the food consumption score has increased since the restoration efforts in 2017.

Table 1 presents the summary statistics for all the variables measuring the economic well-being of households.

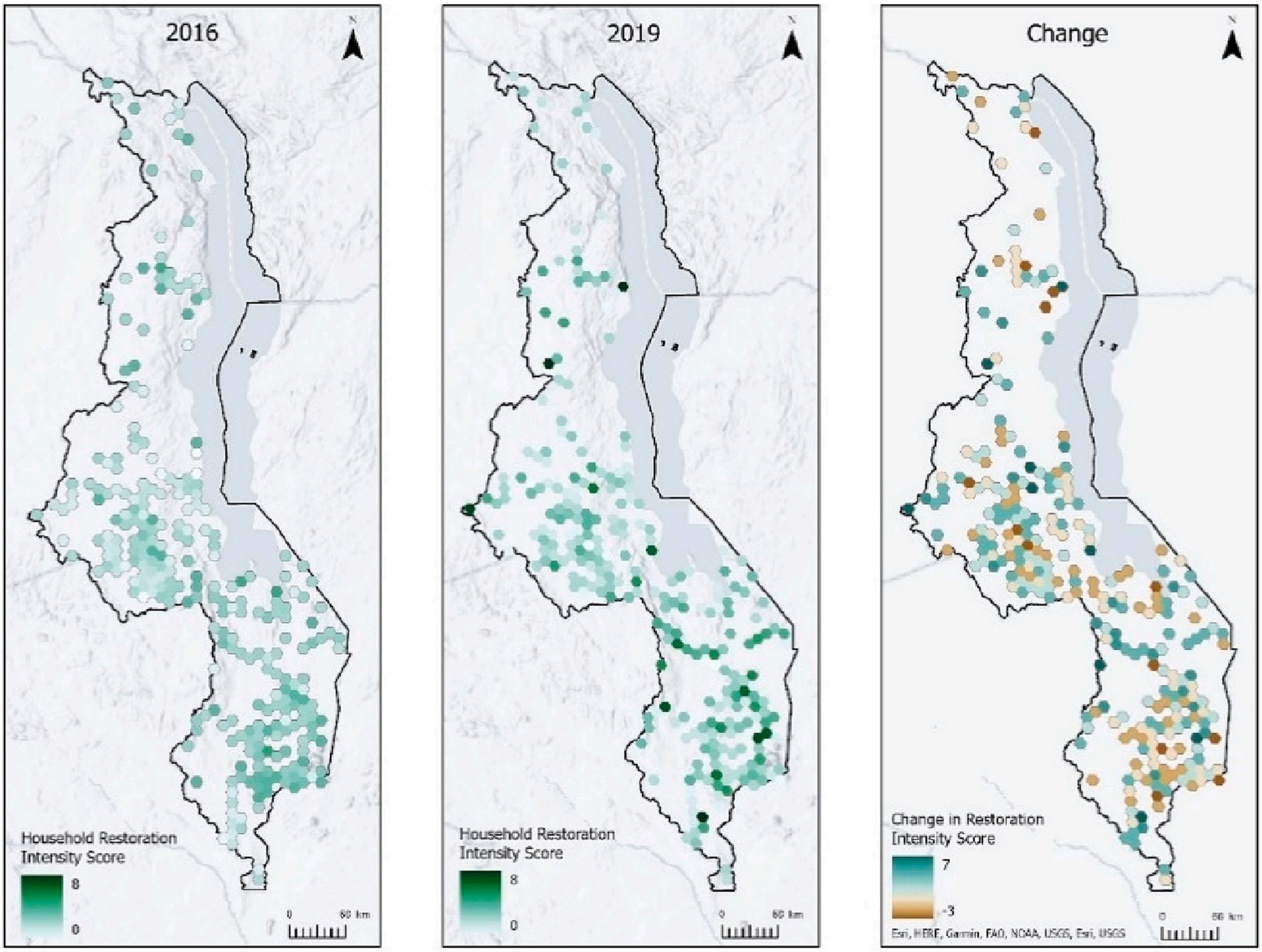

Fig. 4. Spatial distributions of the HRIS in 2016 and 2019, and the change in HRIS between the two years.

2.2. Modelling the causal effects of restoration interventions on the improvement of household wellbeing

2.2.1. The econometric model

To estimate the impact of farmland restoration intervention on household income and food security, a Difference-in-Difference (DiD) method was used to analyze the two-year panel data set. DiD allows for isolating the treatment effect over time, in a way that other methods would not. Issues of data quality prevented the application of other quasi-experimental methodologies that might be used in conjunction with a DiD approach. This application of DiD is not fully quasi-experimental due to the lack of a baseline year t_0, for which the *status quo ex-ante* can be known to establish a causal relation. Also, our 'treatment' variable, the HRIS, is not a binary variable indicating whether a household implemented agricultural restoration or not, but instead a continuous index variable intended to approximate the intensity of restoration efforts on each household's land. The present analysis has been adjusted to account for the characteristics of our model. Two separate econometric models were developed to estimate the causal links between farm-level restoration intensity and the socio-economic impacts at household level in terms of (1) income (*tier-one effect*) and (2) food security (*tier-two effect*), respectively.

2.2.2. Tier-one effect model: Links between restoration intensity and household income improvement

The impact of restoration intensity on household income refers to a *first-tier* effect, as restoration over time can lead to higher agricultural output, which contributes directly to household income. The tier-one effect model is presented in Eq (3).

$$\log Y_{j,t} = \beta_1 * HRIS_{j,t} + \beta_2 * T + \beta_3 * HRIS_{j,t} * T + \beta_4 * C_{j,t} + \delta + \varepsilon \quad (3)$$

where $\log Y_{j,t}$ is the income per capita in the household *j* at time *t*. *T* is time and accounts for temporal trends over the two waves of surveys. $HRIS_{j,t}$ is the household restoration intensity score. $T*HRIS_{j,t}$ captures the interactions between time and household restoration intensity score. $C_{j,t}$ are the control variables representing the characteristics of household in each wave of survey, including variables related to the characteristics of the farm, the household, and the biophysical conditions.

2.2.3. Tier-two effect model: Links between restoration intensity and food security in the household

This study treats food security as a *second-tier* effect, since the food consumption score is dependent on variety of foods, not just subsistence foods, then it implies that greater household income is required to achieve a higher food consumption score. Hence, household income is included in the model as a control variable. The *tier-two effect* model is presented in Eq. (4).

$$\log F_{j,t} = \beta_1 * HRIS_{j,t} + \beta_2 * T + \beta_3 * HRIS_{j,t} * T + \beta_4 * C_{j,t} + \beta_5 * logY_{j,t} + \beta_6 * HRIS_{j,t} * \log Y_{j,t} + \delta + \varepsilon \quad (4)$$

where log Fj,t is the food consumption score in household *j* at time *t*.

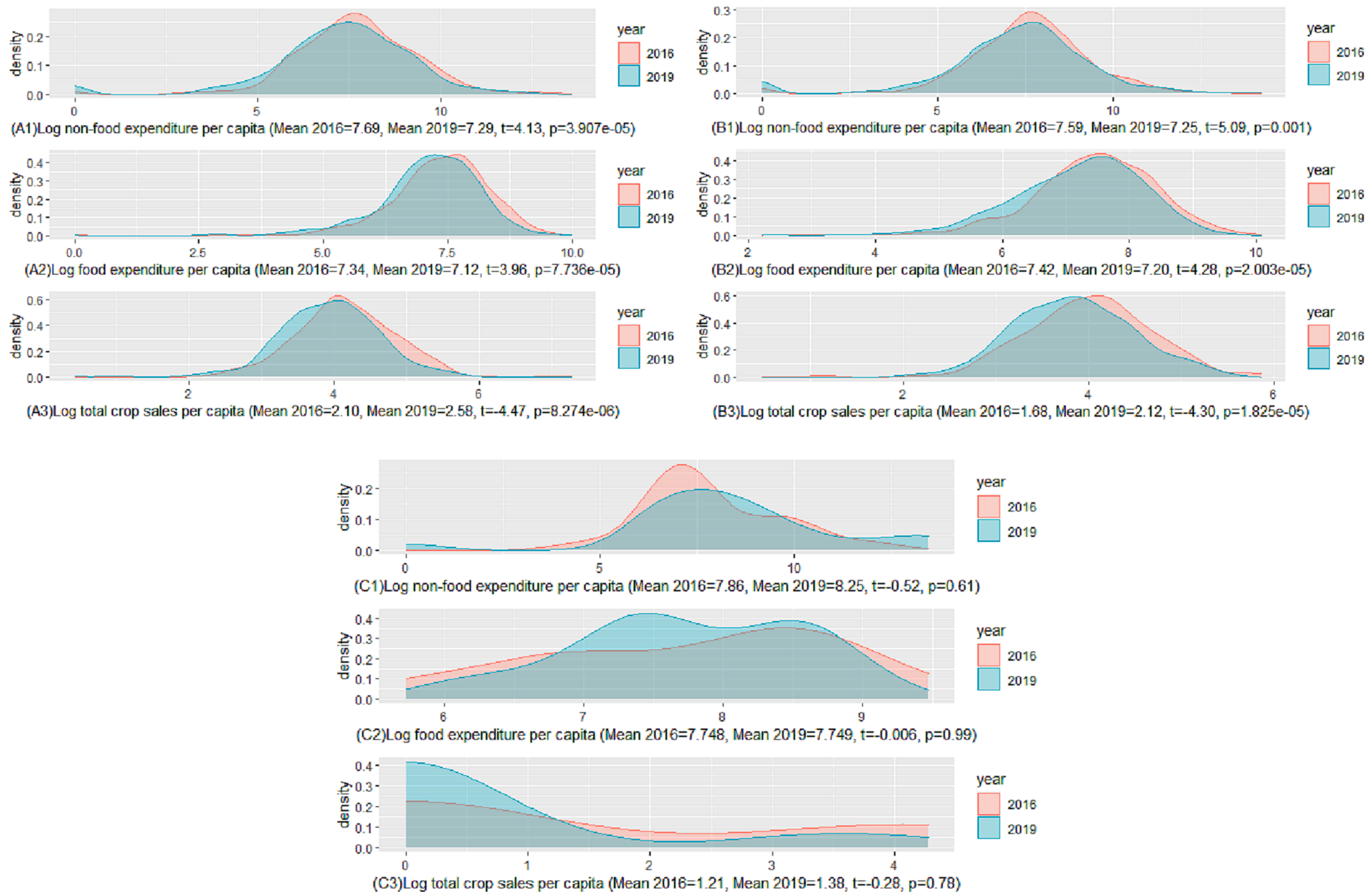

Fig. 5. Distributions of the household non-food expenditure per capita/ household food expenditure per capita/log total crops sales per capita; A1-A3 presents the distribution for households with an increased land restoration intensity score, B1-B3 presents the distribution for households with a decreased land restoration intensity score, C1-C3 presents the distribution for households with unchanged land restoration intensity score.

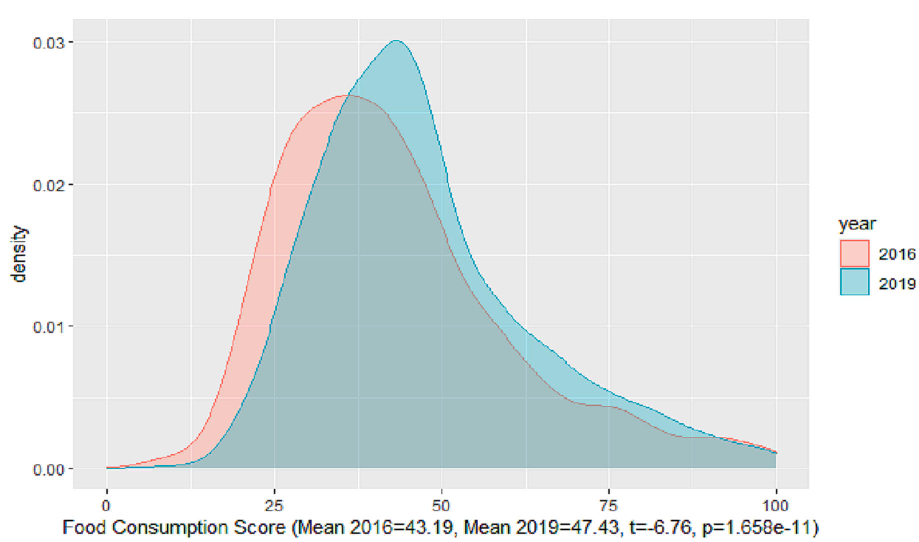

Fig. 6. Distribution of the Food consumption score.

$HRIS_{j,t}*\log Y_{j,t}$ captures the interactions between household restoration intensity score ($HRIS_{j,t}$) and household income.

For both models, other counterfactuals affecting farmer livelihoods are captured through control variables. Control variables in this study are categorized into three subgroups: (a) variables representing household characteristics including household size (adults), sex/age/education of household head, distance to market, access to credit, ganyu labor income[5], (b) variables representing farm characteristics such as

[5] Ganyu labor income refers to labor income from short-term work on other farms or agricultural estates.

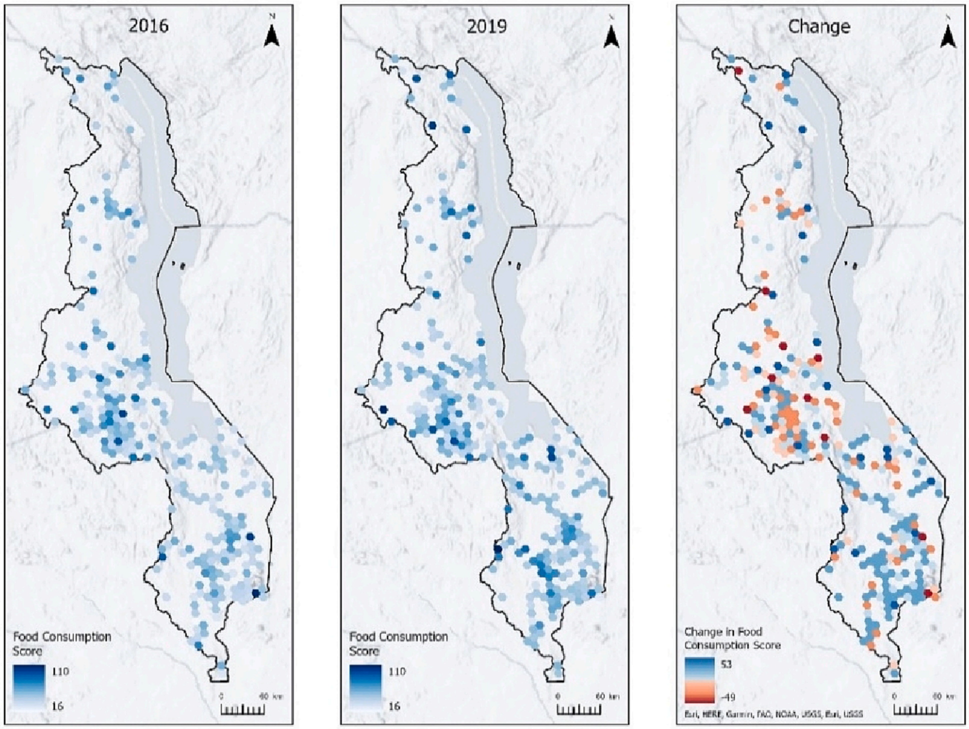

Fig. 7. Spatial distributions of the FCS in 2016 and 2019, and the change in FCS between the two years.

Table 1
Summary statistics for socioeconomic variables.

Variables	Min		Mean		Max		SD	
	2016	2019	2016	2019	2016	2019	2016	2019
HRIS	0.00	0.00	2.05	2.24	20.75	24.73	0.90	1.83
Food expenditure per capita	0.00	0.00	2,461	1,990	23,620	21,501	2,385	1,932
Non-food expenditure per capita	0.00	0.00	9,563	11,224	775,363	1,494,310	39,122	68,631
Sales value of crops per capita	0.00	0.00	35,012	14,544	18,500,000	535,333	526,751	42,931
FCS	6.50	7.00	43.19	47.43	112.00	112.00	17.78	16.83

land area, number of livestock owned (incl. ruminants and poultry), number of fruit/permanent trees owned, and (c) variables representing the biophysical conditions of the household's location including temperature, precipitation, and soil quality. Among all the control variables, only soil quality is measured with an index using Principal Component Analysis (PCA) (See Appendix 4 for details). The other variables are extracted from the original data of the surveys (see Appendix 5 for details). Table 2 presents the summary statistics of all the control variables.

Table 2
Summary statistics for control variables.

Variables	Min		Mean		Max		SD	
	2016	2019	2016	2019	2016	2019	2016	2019
Household size (Adults)	1.00	1.00	2.96	3.01	10.00	10.00	1.37	1.46
Age of household head	15.00	10.00	44.32	46.26	106.00	94.00	15.81	15.52
Sex of household head (1 = FEMALE)	0.00	0.00	0.27	0.28	1.00	1.00	0.44	0.45
Education of household head	1.00	0.00	1.23	1.13	6.00	8.00	0.72	0.90
Distance to market	0	1.00	24.36	24.10	59.00	59.00	14.43	14.25
Access to credit (1 = YES)	0.00	0.00	0.25	0.26	1.00	1.00	0.44	0.44
Ganyu labor income per capita	0.00	0.00	36,660	52,721	5,040,000	4,905,600	151,587	218,273
Land area	0.01	0.01	1.91	1.87	18.00	18.96	1.85	1.76
No. of ruminants	0.00	0.00	1.43	1.36	227.00	200.00	6.61	6.23
No. of poultry	0.00	0.00	3.74	4.08	300.00	147.00	11.45	8.95
No. of fruits trees	0.00	0.00	14.52	20.39	2,076.00	10,001.00	115.46	275.03
No. of cash crop trees	0.00	0.00	6.80	61.93	1,200.00	10,998.00	79.21	376.33
Annual Mean Temperature (C*10)	179	180.00	215.22	214.89	264.00	263.00	18.72	18.58
Annual Precipitation (mm)	778	792.00	1,058.19	1,060.97	1,844.00	1,974.00	232.05	231.87
Soil quality index	0.51	0.51	2.80	2.91	7.21	7.91	1.39	1.35

Table 3
Abridged Difference-in-Differences (DiD) Regressions for Malawi

	Log of Food Expenditure per Capita {1}	Log of Non-Food Expenditure per Capita {2}	Log of Total Crop Sales per Capita {3}	Food Consumption Score {4}
…	…	…	…	…
DiD Estimate: HRIS*Year	**1.948*** (0.514)**	**3.242*** (1.227)**	**2.005* (1.196)**	**36.256*** (9.119)**
…	…	…	…	…
Individual Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	NO	NO	NO
R-squared	0.130	0.062	0.073	0.191
Observations	2,884	2,884	2,884	2,884

3. Results and discussions

3.1. Model results and discussion

Presented in Table 3 are abridged regression results of the DiD model, where each column pertains to a regression and presents the estimated DiD coefficient for each. Regressions (1), (2), and (3) reflect the relationship between HRIS over time and proxies used to assess household income (*tier-one* effects): (1) household food expenditure per capita, (2) household non-food expenditure per capita, and (3) household crop sales per capita. Regression (4) reflects the impact of HRIS over time on the household's food consumption score (*tier-two* effects). *Tier-one* effects are anticipated to contribute, through the respective channels, to the *tier-two* outcome of food security; this is affirmed in the DiD model estimates.

3.1.1. Impacts of land restoration interventions on household income

The impact of HRIS over time on the *tier-one* socioeconomic outcome of household income can be observed in the coefficients from the interaction term between HRIS and Year (i.e., T*HRIS), when regressed on (1) household food expenditure per capita, (2) household non-food expenditure per capita, and (3) household crop sales per capita. In each case, the DiD model estimates a positive and statistically significant effect of HRIS over time on the selected proxies for household income. The DiD estimates show that two years after the adoption of farmland restoration activities in 2017 (or three years after the previous survey wave in 2016), overall agricultural output (as theorized) has been improved, leading to greater crop sales. Increased crop sales translate to greater household income generated by marketed agricultural output, which enables households to consume more food and non-food items that were purchased from the market. Increased consumption of non-food items indicates that a household is in possession of sufficient resources to make goods purchases, which contributes to quality-of-life improvements. Increased consumption of food items from the market can indicate that a household is purchasing a greater quantity, quality, and/or diversity of foodstuffs, which contributes to improved food consumption and quality of life.

Identifying a significant and positive effect from farmland restoration on these *tier-one* outcomes indicates that restoration interventions can effectively stimulate the improvements in a household's income and consumption, transversely improving the overall quality of life in that household. This is an extremely important effect, as overall improvement of household income allows farmers to have more disposal income that can be used not only for reducing immediate food insecurity, but also for adopting restoration interventions on their farms for long-term benefits (Meijer et al., 2015). Demonstrated through the DiD model, a longer-term payoff is observed, which bolsters the overall sustainability of adoption for these interventions, so long as efforts are durable and maintained. However, indications from the model demonstrate that there is a longer-term delayed payoff in farmland restoration interventions. In some cases, more years might be required to fully realize the benefit of adopting at least some restoration initiatives. In our model, the measured delay is for a minimum of three years. In the near-term, the effect of the interventions appears muted to some degree, potentially capturing the initial costs of adoption. Hence, to accelerate farmland restoration at scale, appropriate financial incentives must be provided to cover farmers' initial costs of adoption.

Besides the impact identified from HRIS over time, other variables are observed to have significant contributions to growth in crop sales and expenditures (See unabridged regression table in Appendix 6). For example, significant and positive effects are observed in larger land areas and in the number of ruminant livestock. These effects are consistent with the broad literature and applied theory. Among the controls included as covariates in the models, only the age of the household head has a significant correlation. The reasoning behind this correlation is ambiguous – the effect is inconsequential to the overall findings of this paper. Household access to credit has the expected effect on non-food expenditures, but not on crop sales. This, again, is not a key line of inquiry for this paper, but can indirectly elevate households' socioeconomic well-being by making more funds available for investment in farmland restoration activities and input. Regressions (1), (2), and (3) provide estimated effects from explanatory and control variables that are either consistent with authors' expectations or remain ambiguous, providing the authors with confidence in the models' estimates.

3.1.2. Impacts of land restoration interventions on household food security

Impact of HRIS over time on the *tier-two* outcome for household food security is observed in the coefficient of the interaction term between HRIS and Year, when regressed on (4) household food consumption score. A significant and positive effect from HRIS over time on food security is estimated *via* the DiD model. This DiD estimate provides that farmland restoration activities lead to greater food consumption, by quantity and variety. Food consumption score in this context makes for a clean proxy for overall household food security. Therefore, it can be said that restoration on farmland over time improves household food security.

Farmland restoration activities are not expected to have a direct impact on variety and quality of household food consumption. Rather, these restoration interventions work through various channels in improving agricultural production, which have been demonstrated earlier to affect *tier-one* outcomes for household income. The proxies used to capture characteristics of the *tier-one* outcomes for household income are likewise relevant in accounting for impacts on household food security. Each alone demonstrates a statistically significant and positive effect on household food consumption. Interaction terms between the *tier-one* outcomes and HRIS do not, however, definitively demonstrate that farmland restoration achieves impact on food security through those channels.

As previously observed, a delayed payoff to farmland restoration activities is demonstrated through the DiD model. A few more years might be required to fully realize the benefit of adopting at least some restoration initiatives. Coupled with the existing poverty and food insecurity in Malawi, this delayed payoff might constrain farmers' adoption of restoration interventions, especially the tree-based interventions that might need much longer to reap benefits (Meijer et al., 2015). Thus, short-term financial support should be provided to farmers that are willing to adopt restoration interventions to help them cope with immediate food insecurity. Additional explanatory and control covariates in the model demonstrate effects consistent with the authors' expectations.

3.2. Caveats

While the modelling results are promising, their interpretation needs to be treated with care due to several major caveats. A few key challenges are highlighted below, as they may undermine the robustness of the causal relationship identified by the model.

First, the restoration interventions included in the IHPS surveys provide an incomplete picture of farmland restoration, as the questions are limited strictly to conservation agricultural practices. While farmers reported the number of fruit trees planted on their land, other types of tree-based restoration interventions, including tree planting, FMNR, agroforestry, agro-silvo-pastoralism, or the restoration of community forests or woodlots, are not included in IHPS surveys. Additionally, farmers were only asked about which of the common interventions were performed on their farms rather than how well and intensive each intervention was performed. The poor data quality prompted us to construct household restoration intensity score (HRIS) to present aggregated information extracted from the secondary survey data.

Second, HRIS has its own limitations as it is unable to account for heterogeneity of restoration interventions across households. The HRIS was developed because the IHPS surveys from which we took our data did not include any questions explicitly mentioning restoration. However, survey questions include five types of conservation agricultural practices, which falls under the definition of farmland restoration interventions used for this paper (Fig. 1). This allowed us to repurpose the secondary IHPS data to study the impacts of restoration on socioeconomic outcomes. However, this methodology has the disadvantage of not differentiating between the individual effects of each type of intervention. It assumes that all interventions have the same level of impact on the land, thus the variation of HRIS is affected by the quantity of interventions rather than the quality of restoration. Additionally, the score's continuous nature prevented us from distinguishing households between distinct control (no restoration) and treatment (restoration performed) groups.

Third, data incompatibility exists for some biophysical indicators collected at different scales. For instance, changes in crop yields can only be measured at the individual plot level, which is incompatible with data on farmland restoration interventions that are reported at the household level. This prevented us from singling out the causal effect of individual restoration interventions at the plot level on a household's increased agricultural production and sales. Additionally, while the yield of each crop type and the overall field size were given, the information of cultivated field area for each crop was missing. This prevented us from getting an accurate measure of crop yields at the household level, which would have allowed for a better understanding of restorations interventions' direct impacts on agricultural productivity.

Fourth, the three proxies of household income are not the best indicators to measure household income improvement. Real household income improvement is reflected in the real purchasing power of the household, which is often measured by disposable income of the household that in part can be derived from increased agricultural outputs.

Fifth, the Food Consumption Score used in this study measures the current status of household food security at the time when the interview was conducted but does not attribute to long-term restoration efforts. It is calculated based on the recalled food consumption frequency in a 7-day period, hence the score is largely affected by when, where, and to whom the survey questions were presented.

Lastly, a longer timeframe is needed for socioeconomic impact assessment due to the lagged effects of farmland restoration. The socioeconomic data used in this analysis were collected only two years after Malawi's national Forest and Landscape Restoration Strategy was implemented, which is rather short for capturing the fully realized effects of restoration interventions on farms. Although most agricultural interventions included in the IHPS surveys are seasonal and can generate effects much sooner than many tree-based interventions such as agroforestry, the short timeframe considered for this analysis does reduce the likelihood of ruling out other counterfactuals that may have also contributed to the positive socioeconomic outcomes.

4. Conclusions and future research

This research developed an analytical framework and a DiD model to analyze the causal effects of the farmland restoration interventions on the socioeconomic improvement of affected rural population. While the framework and the model can be applied to assess the impacts of farmland restoration at any geographical locations, they were carefully tested in this paper through a special case in Malawi. In 2017, the country made 4.5-million-hectare restoration pledge, of which about 45% is on farmlands. Additionally, the analysis explored the potential of using the secondary household survey data to identify key socioeconomic indicators for tracking socioeconomic improvement associated with farmland restoration progress over time. In particular, IHPS survey data from two periods, i.e., 2016–2017 (before the restoration pledge) and 2019–2020 (after the restoration pledge), was used for the economic analysis.

Overall, the model shows some promising results. All four regressions generated statistically significant results regarding the positive impact of restoration interventions over time on four socioeconomic indicators, including food and non-food expenditure, crop sales, and food consumption score at the household level. This suggests that farmland restoration interventions are having a positive impact on soil productivity and agricultural outputs over time. These positive effects are then translated to improved socioeconomic outcomes for local households as expected. The statistical significance of the causal relationship indicates that the selected socioeconomic indicators are very relevant for tracking landscape restoration progress on farmland.

Despite these positive effects, data limitations do not allow us to draw conclusions on whether restoration interventions have directly contributed to the economic growth observed since 2017. Especially, the IHPS surveys provide only aggregated household income, of which the portion that is associated with restoration-related efforts could not be isolated. Hence, the casual relationship between restoration interventions and direct income growth remains inconclusive. Subsequently, the model results should also be interpreted with care due to clear caveats on secondary household survey data (Section 3.2). Our analysis suggests that secondary data without purpose-created indicators do not fully reflect the nuances of restoration implementation on farms or the socioeconomic status of the households being surveyed, which may undermine the robustness of the observed causal effects.

However, findings from the Malawi case shed lights on three specific ways, in which existing household surveys can be improved to tackle some of the socioeconomic data challenges associated with restoration impact assessment:

(1) To better understand the impacts of farmland restoration on household income, respondents should be asked to differentiate the sources of household income, as opposed to the total income currently included in the IHPS surveys.

(2) Alternative indicators to the existing food consumption data in household surveys should be developed to measure long-term food security, taking into account at least several years after restoration interventions have been implemented to fully capture their effects.

(3) Additional socioeconomic data collection is needed for omitted variables such as political economy context of the country, family and cultural tradition, social norms, education, health conditions, and access to resources and markets that all could affect the adoption rates of restoration interventions at household level and the success of their implementation in the field. These unfortunately were excluded from the current analysis due to limited availability and quality of data collected through the IHPS surveys.

In addition to these needed improvements in household surveys, continuous research would also be required to address data quality issues around restoration. For instance, the construction of household restoration intensity score (HRIS) in this study suggests that more specific information on restoration implementations needs to be collected to better gauge the quality and effectiveness of the intervention. This might not be directly tackled through household surveys that specifically focus on socioeconomic data collection, but potentially through other global data initiatives such as The Economics of Ecological Restoration (TEER), which aims to standardize the restoration-related economic data collection at project level. Moreover, future data innovations should focus on how different datasets could be collected in a compatible way to ease the causal-effect analysis between restoration interventions and socioeconomic impacts. In this regard, donor communities and impact investors could play an important role in setting up dedicated and continuous research funds for advancing socioeconomic research and addressing additional data needs. These efforts might seem costly in the interim, but more plausible and far more rewarding than repurposing existing household survey for restoration impact assessment.

In sum, this paper calls for urgent global efforts to advance socioeconomic research on standardized guidelines, indicators, and monitoring structure; continue R&D on socioeconomic data innovation; and accelerate the process to improve socioeconomic data collection techniques. These efforts will allow better project-level monitoring of restoration progress. While some modest progress has been made, the speed that large scale landscape restoration projects are being developed and deployed largely outpaced the speed of filling the existing data gap. Developing better ways of collecting socioeconomic data at scale and analyzing the impacts of restoration on socioeconomic outcomes is vital to ensuring that the global community meets its crucial targets under the UN Decade on Ecosystem Restoration.

CRediT authorship contribution statement

Helen Ding: Conceptualization, Methodology, Writing – original draft, Supervision, Project administration. **Tian Yu:** Software, Formal analysis, Data curation, Writing – original draft. **Darby Levin:** Visualization, Data curation, Writing – original draft. **James Warburton:** Methodology, Software, Formal analysis, Writing – original draft. **Katie Reytar:** Writing – original draft, Visualization, Funding acquisition. **Rong Fang:** Software, Formal analysis. **Holly Keifer:** Investigation. **Bernadette Arakwiye:** Writing – review & editing. **Spencer Ngoma:** 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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110068.

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