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# Forest pattern, not just amount, influences dietary quality in five African countries

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## 1. Introduction

There are now far more people across the planet who suffer from micronutrient deficiencies or are overweight or obese than there are people who are hungry or under-nourished (Development Initiatives, 2017). Low dietary quality is a serious concern as it is one of the main risk factors for morbidity and mortality globally (Forouzanfar et al., 2016; WHO, 2005; Stanaway et al., 2018). Central to dietary quality is dietary diversity, which is linked to nutrient intake at the individual level across a wide range of settings (Arimond et al., 2010). Fruit and vegetable consumption are particularly important contributors to dietary diversity, but frequently consumed far below recommended levels (Willett et al., 2019), especially in Africa (Hall et al., 2009). In a study of 52 low- and middle-income countries, about 80% of people failed to meet the recommended intake of fruit (Hall et al., 2009). Moreover, while the global production of staple foods is sufficient to meet the requirements of current and future global populations (Berners-Lee et al., 2018), production of fruits and vegetables is presently insufficient, providing only 66–78% of global fruit requirements (Siegel et al., 2014). Inadequate fruit and vegetable consumption has serious health implications, with up to 2.6 million deaths per year attributable to inadequate intake (Lock et al., 2005). Fruit intake is also linked to improved micronutrient intake, and lower risk of overweight, obesity and associated chronic disease (Lock et al., 2005; Fulton et al., 2016).

Many low- and middle-income countries are currently in the midst of a nutrition transition—in which traditional diets rich in vegetables, pulses and legumes, and fruits are being replaced with poorer quality diets excessive in calories, fats and oils, and sugar (Cockx et al., 2018; Steyn and Mchiza, 2014; Abrahams et al., 2011). Simultaneously, there is continuing debate about how best to feed the world in a sustainable manner (Balmford et al., 2018; Pretty et al., 2018; Mehrabi et al., 2018). Balancing dietary diversity with low environmental costs is thus paramount, but requires a better understanding of the environmental drivers of diets. While people's dietary diversity is generally positively associated with their wealth status, market integration, and on-farm crop diversity (Jones, 2017; Powell et al., 2015; Sibhatu et al., 2015), recent work has shown that for rural communities in low- and middle-income countries, intensification of agricultural production does not necessarily lead to positive diet outcomes (e.g., Broegaard et al., 2017). In fact, increasing agricultural production might lead to poorer diets because of a shift to monoculture cash crops, rather than diversified production and consumption (Kennedy et al., 2007; Lachat et al., 2018; Pingali, 2015; Jones et al., 2014; Powell et al., 2015; Ickowitz et al., 2016; Khoury et al., 2014).

Increasing agricultural production is also a leading cause of forest loss and fragmentation (Curtis et al., 2018). As many tropical forests are 'the supermarket of the wild' (Wunder et al., 2014), forest loss and fragmentation might further reduce dietary diversity by reducing the availability of wild foods (Broegaard et al., 2017; Ickowitz et al., 2016). Yet, the pathways by which forests contribute to people's diets go far beyond wild food in also providing: 1) fodder for livestock which then provide meat, milk and eggs, as well as manure to improve agricultural production and crop nutritional quality (Baudron et al., 2017; Wood

and Baudron, 2018); 2) ecosystem services, such as pest control (Bianchi et al., 2006; Maas et al., 2013; Ricketts et al., 2008) and nutrient cycling, which in turn may improve agricultural productivity (Reed et al., 2017) and crop nutritional quality (Wood and Baudron, 2018); 3) high-value products that can be sold and thereby enable food purchases (Rasmussen et al., 2017); and 4) fuel wood for slow-cooking foods e.g. legumes and beans (Remans et al., 2012; Arnold et al., 2011). This contribution of forests and trees to dietary quality is becoming increasingly recognized (Golden et al., 2011; Powell et al., 2015; Rowland et al., 2016; HLPE, 2017) and a growing number of studies have examined the links between forests and diets. Across Africa, Ickowitz et al. (2014) demonstrated that children's dietary diversity correlated positively with percentage tree cover surrounding their communities and Galway et al. (2018) showed that child dietary diversity was negatively correlated with forest loss. Moreover, Rasolofson et al. (2018) estimated that living in an area with high forest cover increased the dietary diversity of children at least 25% compared to those in low forest areas. These studies focused on the amount (proportion) of forest in the landscape, but did not examine if and how the spatial arrangement of that forest influences dietary outcomes.

There are strong theoretical reasons to expect that the arrangement of forests across a landscape could affect diets – perhaps to an even greater extent than the amount of forest. Forest configuration (the size and arrangement of forest patches across a landscape) heavily influences many socio-ecological processes, including wildlife movement, pollination, seed dispersal, and human access to forest resources (Fahrig, 2017; Fletcher et al., 2018). Forest fragmentation (the breaking of larger blocks of forest into smaller patches) is a critical aspect of configuration, caused primarily by logging, agricultural expansion, and the development of roads and other infrastructure (Potapov et al., 2017). Fragmentation has been shown to reduce biodiversity and ecosystem function (Haddad et al., 2017) which in turn could reduce the availability of wild foods such as forest-dependent animal species (Parry et al., 2009). Yet, smaller blocks of forests might better support people's diets if people collect food and products along forest edges; many non-timber-forest-products, for example, are primarily extracted from smaller forest patches (Milheiras and Mace, 2019). The spatial arrangement of forests can thus affect the food available and the way that people access forest resources or manage agricultural production, yet it is not known whether household diets, for example, benefit more from one large patch of forest or several smaller patches of forest in the surrounding landscape.

This is the first study to our knowledge that empirically examines the impact of both forest cover and configuration on local diets. Specifically, we examine how both the proportion and spatial arrangement of forest in a given landscape is related to people's dietary diversity. We use the consumption of fruits as an important sentinel food group likely to be influenced by forest proportion and configuration. We hypothesize that people's dietary diversity and their likelihood of consuming fruits are associated with local landscapes that have 1) a greater extent of forest cover, and 2) more edge habitat and smaller blocks of forest. To empirically test our hypotheses, we conducted a multi-country assessment across five African countries, spatially linking household data on food consumption, agricultural production and assets from the World Bank Living Standard Measurement Surveys (LSMS) with forest cover and configuration metrics extracted from global datasets (Hansen et al., 2013). Testing these hypotheses is a step forward in understanding linkages between forests and people's dietary diversity as we move beyond simply focusing on percentage tree cover. Such enhanced understanding facilitates an improved design of policies aiming at achieving increased dietary diversity for rural populations in tropical low-income countries.

## 2. Methods

### 2.1. Construction of dietary diversity indicators

We used publicly available data from the LSMS (<http://microdata.worldbank.org/index.php/catalog/lsms>), which implements nationally representative household surveys to collect a wide array of livelihood data, including details on household food consumption. We focused on five African countries with geo-located LSMS data and tropical forest: Tanzania, Uganda, Nigeria, Malawi, and Ethiopia. In each country, surveys were completed between 2011 and 2016 with a range of 1886 rural households in Nigeria to over 10,000 rural households from Malawi (Table S1).

The LSMS dataset presents a unique opportunity to compare household diet across countries. It records what people ate at the household level over the past seven days. LSMS offers advantages over other sources of data including: large sample sizes, extensive data on a diverse set of non-diet variables, and a disaggregated record of individual foods, which permits the calculation of different dietary diversity scores (see below). In particular, the disaggregated record of individual foods allows for an enhanced understanding of which types of foods contribute to each food group and the potential mechanisms driving observed relationships (which is less possible with e.g. data from the Demographic and Health Surveys, as noted by Ickowitz et al. (2014)). For example, to try to distinguish whether the relationships between fruit consumption and forest cover and/or configuration are due to consumption of fruit grown on domestic trees or wild fruit, using the LSMS, we are able to disaggregate data on mango consumption (the most commonly consumed fruit from a cultivated tree) and wild fruit. Dietary diversity is defined as the number of food groups consumed over a fixed time period, generally ranging from 24 h to seven days. At an individual level, dietary diversity can be considered a proxy for micronutrient adequacy of the diet (Arimond et al., 2010) which is considered one aspect of diet quality. As individual data are not available in LSMS, we constructed a modified household dietary diversity score (MHHDS) using the ten food groups recommended to construct MDD-W (Minimum Diet Diversity of Women) (FAO and FHI 360, 2016) but based on a recall of the past seven days. Household diets are highly correlated with individual diets, however, household-level dietary diversity does not account for issues of intra-household distribution and should not be used for statements concerning particular population groups, such as women (Verger et al., 2019). The MHHDS includes the following ten food groups: 1) starchy staple foods (cereals, white roots, tubers, plantains), 2) other vegetables, 3) flesh foods, 4) other vitamin A-rich vegetables and fruits, 5) pulses (beans and peas), 6) nuts and seeds, 7) dairy, 8) eggs, 9) dark green leafy vegetables, and 10) other fruits (FAO and FHI 360, 2016) (Figs. S1A–B). To check the robustness of our results, we also assessed our models with the 12-group Household Diet Diversity score (Swindale and Bilinsky, 2006) (Table S4).

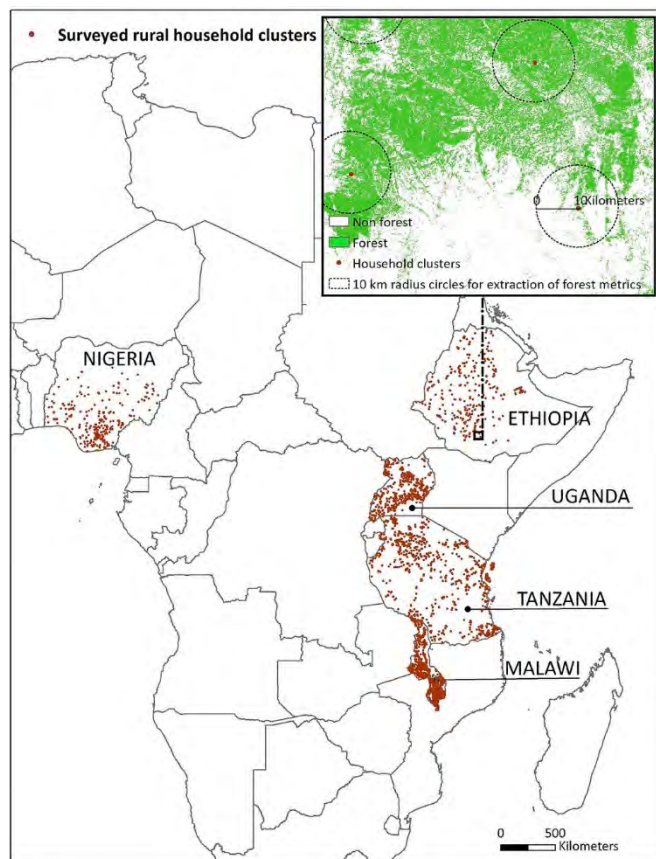
In addition to dietary diversity, we examined the consumption (presence/absence) of fruits over the last seven days, which we expect

is likely to be associated with forest cover and configuration (Powell et al., 2015; Ickowitz et al., 2014, 2016). While vegetables and animal source foods are likewise assumed to be associated with forest cover, almost all household consumed vegetables in the last seven days and the consumption of bushmeat is not well recorded in the LSMS data and thus we could not test for a relationship using presence/absence.

## 2.2. Measurement of forest cover and configuration

Data on forest cover in the year of the LSMS survey was obtained from a publicly available 30 m resolution global tree cover dataset from 2000 to 2016 (Hansen et al., 2013). We downloaded tiles covering the spatial extent of our five study countries and derived tree cover in the year of the LSMS survey by masking water, adding forest cover gain and subtracting forest cover loss from the base year 2000. The data show the percentage tree cover in each pixel with trees defined as vegetation taller than 5 m. To create a forest cover map, we classified each pixel to a binary forest/no forest classification, using a ‘forest’ threshold definition of 30%. We tested other thresholds (10% and 60%), based on common thresholds used by the United Nations Food and Agricultural Organization and United Nations Framework Convention on Climate Change (FAO, 2000; FAO, 2005). We chose 30% as it resulted in forest cover maps that best matched country-level land cover maps where available. Because global products on tree cover (such as the Hansen dataset) are not designed to capture tree cover in woody savannahs and other sparse vegetation, and performs poorly in these landscapes, the northern part of Nigeria was excluded from the analysis.

The LSMS survey uses a ‘cluster’ of households (in most cases corresponding to a village) as the sampling unit. The georeferenced points for 99% of cluster locations have been randomly displaced by 0–5 km for confidentiality purposes, and to a maximum of 10 km for the remaining 1% of clusters. We thus measured forest cover and configuration in a 10-km radius circle surrounding each cluster (Fig. 1) to account for this random spatial displacement as well as to capture a reasonable distance that people were likely to travel for hunting and collecting wild foods (Layton et al., 1991). We used Fragstats 4.2 (McGarigal et al., 2002) to extract percentage forest, number of forest patches, edge density, total forest edge, average patch size, and perimeter-area ratio metrics for each landscape. These metrics were chosen as they capture different dimensions of forest configuration and thus yield insight on various aspects related to the availability of forest resources and forest access. To check the robustness of our analyses, we reran all analyses using a 5 km radius and found similar results.



**Fig. 1.** | Geographic locations of rural clusters. The World Bank’s Living Standard Measurement Study used a cluster of households as the geographical sampling unit which we spatially linked to forest metrics in a 10 km radius circle.

### 2.3. Covariates influencing dietary quality

Several household and geographical characteristics are known to influence dietary diversity as well as the consumption of wild foods (Cooper et al., 2018). We controlled for these covariates—or their proxies—to the extent possible with available data (Table 1). For household characteristics, we controlled for household size, age, gender of head of household (Workicho et al., 2016; Malapit et al., 2015), and highest educational level of the household head (Torheim et al., 2004; Workicho et al., 2016). Because wealthier households might be able to purchase more costly nutrient-rich foods, we also constructed an asset-based wealth score as a proxy for households' long-term economic status. The number and type of assets included differed by country as the LSMS asset module is country-specific. For a full list of the assets we included in the wealth score in each country, see Table S2. Following Filmer and Pritchett (2001) all household assets were dichotomized to indicate the ownership of each, and we then used a principal component analysis (PCA) to compute wealth groups (Table 1). We chose an asset-based score as it has been shown to be a good proxy for the wealth of a household over time and is less susceptible to measurement error than income data (Hjelm et al., 2016). Moreover, metrics such as proportion of income spent on food might be problematic as households tend to spend proportionally less on food as their disposable income increases (Smith et al., 2014). Because farm production diversity has been documented to be positively associated with dietary diversity (Jones et al., 2014; Sibhatu et al., 2015), we included the number of crops cultivated by each household. As the consumption of certain food groups and food items may be sensitive to seasonal variations (Savy et al., 2007; Nyambose et al., 2002), we also controlled for seasonal dietary patterns by including the calendar month of the household survey.

We controlled for geographical variables, including precipitation, temperature and soil nutrient availability (Table 1), as these can affect agricultural practices and yields as well as the availability of wild foods. We also used distance to the nearest major road and to nearest population center with more than 20,000 inhabitants as proxies for market access, which tends to improve household income and thereby may facilitate diverse food purchases (Sibhatu et al., 2015).

### 2.4. Statistical models

We examined if forest cover and configuration were associated with MHHDDS (Modified Household Diet Diversity score) and fruit consumption, controlling for household and geographical factors as noted previously. All regression models were estimated separately for each country because the LSMS is not standardized across countries. We estimated the following regression model in one LSMS survey year for each country:

$$Y_{ij} = \alpha + \beta F_{cj} + \mu P_{cj} + \rho D_{ij} + \sigma C_{ij} + \phi M_{ij} + \tau A_{cj} + \theta R_{cj} + \varepsilon_{ij}$$

Where  $Y_{ij}$  represents the two diet quality indicators (diet diversity score and fruit consumption) for rural household  $i$  in country  $j$ ;  $F_{cj}$  is the percent forest cover and  $P_{cj}$  is one of the five forest configuration metrics (included one by one because of collinearity among the metrics) at the cluster level  $c$ ;  $D_{ij}$  is a vector of socio-demographic household characteristics;  $C_{ij}$  is the number of crops cultivated by the household;  $M_{ij}$  is the month that the household was interviewed;  $A_{cj}$  is a vector of two market access indicators; and  $R_{cj}$  is a matrix of geographical characteristics at the cluster level;  $\varepsilon_{ij}$  is a random error term.

Given that the diet diversity score was a discrete variable bounded between one and ten (no households consumed zero food groups within the past 7 days), we used maximum likelihood estimation of Poisson regression models. For models of fruit consumption, we first used logit models with a binary consumption/no consumption classification as the response variable. We also modeled the number of days in which the household ate fruits, using a negative binomial model because of a large dispersion of the variable. For specific food items (mangoes and wild fruits), we used logit models and multiple linear regression to model consumption/no consumption and quantities consumed.

Standard errors were clustered at the level of the LSMS cluster to account for correlation between households within a cluster. All covariates were selected *a priori* based on existing literature on factors known to be associated with household dietary diversity and potential confounding factors on the relationship between forests and dietary diversity. We used a forward and backward AIC-based model-selection approach to evaluate 1) which variables to include, and 2) whether the inclusion of a forest configuration variable resulted in a better performing model. In other words, we tested models that included either a) forest cover alone, b) one of the configuration metrics (included sequentially), and c) both forest cover and one configuration metric (included sequentially). In extended model specifications, we included square terms of forest cover and configuration metrics to account for potential nonlinearities in the relationship (Ickowitz et al., 2014). We also tested an extended specification in which we included an interaction term between forest cover and each of the five configuration metrics. We used both a pairwise correlation matrix as well as the Variance Inflation Factor (VIF) to assess potential collinearity among the independent variables included in our models after fitting regressions. Variables were removed if the correlation coefficient was  $> 0.5$  or/and VIF exceeded a value of 10. As for the potential collinearity between forest cover and forest configuration, we note that Smith et al. (2009) demonstrate how multiple regression performed as well or better than methods used to account for collinearity between these variables. The statistical significance of associations was reported at the  $P < 0.01$ ,  $P < 0.05$ , and  $P < 0.1$  levels. All analyses were carried out in the software R-Core Package 3.4.2 (R Core Team, 2017).



**Table 1**  
**Variables included in regression models.** For each variable the following is described: data source, unit, description of how metric was constructed, and spatial level at which variable was included in our models.

	Data source	Model variable	Unit	Construction of metric	Spatial scale
Dietary variables	LSMS	Diet diversity score	Score ranging from 1 to 10 (MHHDDS) and from 1 to 12	Reclassification of food items into groups: 1) starchy staple foods (cereals, white roots, tubers, plantains), 2) other vegetables, 3) foods, 4) other vitamin A-rich vegetables/fruits, 5) pulses (peas), 6) nuts/seeds, 7) dairy, 8) eggs, 9) dark green leafy and 10) other fruits. Score is a count of these food groups. The 12-group score also includes unhealthy food groups, and it not distinguish between different types of fruits and vegetables	Household
		Fruit consumption	Binary: consumption=1, no consumption=0	Reclassification of fruits items into 1 overall fruit category. Construction of binary variable.	Household
		Days with fruit consumption	Number of days	Directly extracted	Household
		Mango consumption	Binary: consumption=1, no consumption=0	Directly extracted	Household
		Wild fruit consumption	Binary: consumption=1, no consumption=0	Directly extracted	Household (only Malawi)
		Quantity of wild fruit consumption	kg	Conversion to kilograms on the basis of unit conversion data for nonstandard measurement (Joy et al., 2015)	Household (only Malawi)
Forest variables	Hansen et al. (2013) Use of Fragstats to extract metrics in a 10 km radius circle surrounding each cluster	Forest cover	%	Using a ‘forest’ threshold definition of 30%	Cluster
		Number of forest patches	Number of patches	Using an 8-cell neighbor rule for delineating patches	Cluster
		Edge density	m/ha	Using an edge-depth of 100 m	Cluster
		Total edge	m	Using an edge-depth of 100 m	Cluster
		Average patch size	ha	Using an 8-cell neighbor rule for delineating patches	Cluster
		Perimeter-area ratio	Ratio		Cluster
Control variables	LSMS	Gender of head of household	Binary: male = 1, female = 0	Directly extracted	Household
		Age of head of household	Years	Directly extracted	Household
	LSMS	Household size	Number of people	Counting the total number of listed household members	Household
	LSMS	Household wealth group	Categorical	Following Filmer and Pritchett (2001), household assets were dichotomized to indicate ownership of each (1 = owned, 0 = not owned). Type of roof material and toilet facilities were likewise dichotomized (1 = Modern, 0 = Non-modern (including no roof no toilet or shared facilities)). Principal component analysis (PCA) compute wealth quintiles which were then re-coded into three wealth groups: bottom wealth (1. and 2. quintile), middle wealth (3.and 4. quintile), and top wealth (5. quintile).	Household
	LSMS	Number of crops	Count	Counting the number of cultivated crops	Household
	LSMS	Education level of household head	Categorical	Recoding educational levels into 4 comparable categories: none, primary, secondary, and post-secondary	Household
	Geographical variables produced by LSMS team using cluster GPS locations and the following data sources: World Gazetteer Towns, WorldClim Global Climate Data available at <a href="http://www.worldclim.org/">http://www.worldclim.org/</a> (Hijmans et al., 2005), the FAO Harmonized World Soil Database <a href="http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-soil-database-v12/en/">http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-soil-database-v12/en/</a> .		Distance to roads,	Distance measure	Cluster
		Distance to city			
		Mean annual precipitation	mm	Precipitation and temperature are averaged from 1970 to 2000. Spatial resolution of 1 km	Cluster
		Mean annual temperature	°C		
		Soil nutrient availability	Categorical	Categorization based on: Topsoil (0–30 cm): Texture/Structure, Organic Carbon, pH and Total Exchangeable Bases, Subsoil (30–100cm): Texture/Structure, pH and TEB.	Cluster
	LSMS	Month of survey	Categorical	Directly extracted	Household

### 3. Results

The mean 7-day MHHDDS ranged from  $5.6 \pm 1.8$  to  $5.8 \pm 1.6$  in Malawi, Uganda, Tanzania, and Nigeria, but was slightly lower ( $4.8 \pm 1.5$ ) in Ethiopia (Table S1 for both MHHDDS and 12-group Diet Diversity Score). For most food groups, there was an increase in the percentage of households consuming the food group as the dietary diversity increased (Fig. 2). One notable exception was cereals/tubers as nearly all households consumed this food group (97–100%) (Fig. S1). At the highest 7-day MHHDDS of nine consumed food groups, the least consumed food group varied between countries: nuts and seeds in Ethiopia, eggs in Uganda and Tanzania, and dark green vegetables in Nigeria and Malawi.<sup>1</sup> Importantly, fruit consumption was very uncommon for any household with a MHHDDS less than four (Nigeria and Malawi) and six (Uganda and Ethiopia). In Tanzania, fruit consumption was more common, even among households with a very low MHHDDS. Forest cover in a 10 km radius around household clusters varied widely within and among countries, ranging from a national average of  $11\% \pm 14$  in Malawi to  $35\% \pm 28$  in Uganda. All countries, except for Malawi, contained some clusters located in heavily forested landscapes ( $> 75\%$  forest). The spatial arrangement of forest also varied across countries. For example, the average patch size was notably lower in Malawi ( $2.8 \text{ ha} \pm 4.1$ ) and Tanzania ( $7.9 \text{ ha} \pm 15.6$ ) as compared to the other countries, which ranged from  $17.8 \text{ ha} \pm 74.2$  to  $32.3 \text{ ha} \pm 157.1$ . As expected, there was a non-linear relationship between forest cover and configuration in all countries; for example, the number of forest patches increased with forest cover, reaching a maximum at around 20–40% forest cover, with the number of patches declining thereafter (Fig. S2).

#### 3.1. Forest cover and configuration matters for diets

The effects of forest cover and configuration on the MHHDDS varied by country (Fig. 3). Forest cover was positively related to the MHHDDS ( $P < 0.01$ ) in Ethiopia and Uganda with the MHHDDS increasing by 0.14 and 0.15%, respectively, for every additional percentage of forest cover (Table S3). For an average household in Ethiopia with 17% forest cover and a MHHDDS of 4.8, it would be an increase of MHHDDS by 0.007 for an additional percentage forest cover. In Tanzania, the MHHDDS decreased by 0.09% for every additional percentage of forest cover ( $P < 0.01$ ). In Malawi, the MHHDDS decreased with more forest ( $P < 0.05$ ) until a peak of about 22% forest after which the MHHDDS increased – however only 17% of the households have more than 22% forest in their surrounding landscape. Forest cover did not influence the MHHDDS in Nigeria.

We retained only the best-fit model of forest configuration metrics for each country. In the best-fit model for each country, the number of forest patches was the strongest predictor of all configuration metrics tested. It was significantly related to MHHDDS in Uganda, Ethiopia, and Nigeria, but not in Tanzania and Malawi. When controlling for percentage forest cover, one additional forest patch per  $\text{km}^2$  was associated with an increase in MHHDDS of 0.7% in Uganda ( $P < 0.05$ ), 1.0% in Ethiopia ( $P < 0.01$ ), and 1.2% in Nigeria ( $P < 0.01$ ). For an average household in Nigeria with 4 forest patches per  $\text{km}^2$  and a MHHDDS of 5.7, it would be an increase of MHHDDS by 0.07 for every additional patch. When using the 12-group household Dietary Diversity Score, we observed similar trends for the effects of forest cover and number of forest patches in Ethiopia, Uganda, and Nigeria (Table S4). In Tanzania, no significant associations were found, and in Malawi only the square term of forest cover had a statistically significant effect, yet minor.

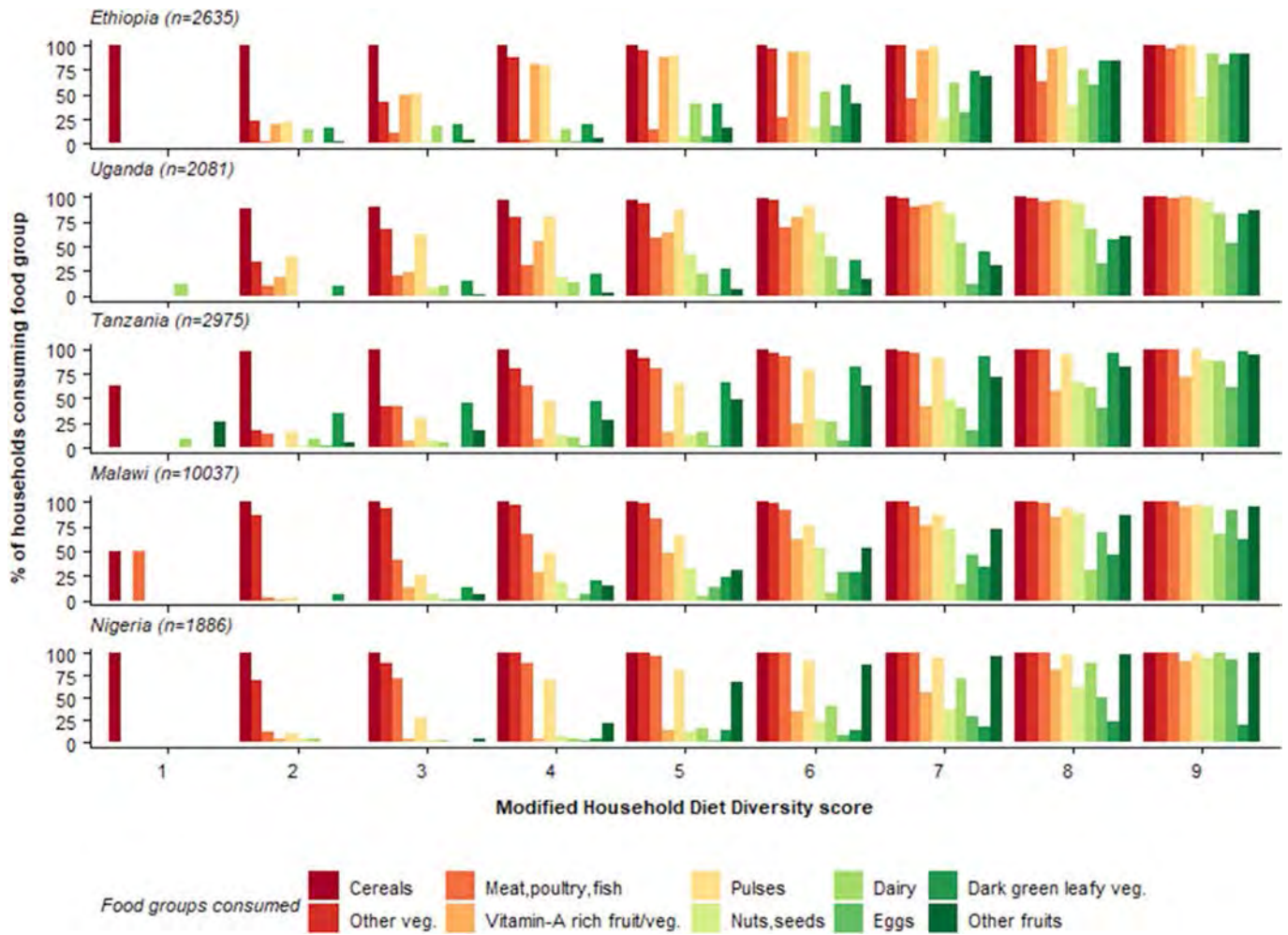
Forest cover was positively and significantly associated with fruit consumption in 4 of the 5 countries ( $P < 0.01$  in Ethiopia, Uganda, and Tanzania, and  $P < 0.05$  in Malawi, Table S5). Yet, the effect was small: each additional percentage of forest cover increased the odds of consuming fruits in the past week by 1–2%. The number of forest patches was also significantly and positively associated with consumption of fruits across four of the five countries. One additional forest patch per  $\text{km}^2$  increased the odds of consuming fruits by 3% in Tanzania ( $P < 0.1$ ), 7% in Uganda ( $P < 0.01$ ), 23% in Nigeria ( $P < 0.01$ ), and 33% in Ethiopia ( $P < 0.01$ ). In Nigeria and Ethiopia, the quadratic effect of the number of forest patches was significant (that is, fruit consumption increased then declined with the number of forest patches), reaching its peak at around 11 patches per  $\text{km}^2$ . Yet, we note that in these two countries relatively few households—less than 10 and 2% of the households, respectively—had more than 11 patches per  $\text{km}^2$  in the 10 km radius circle surrounding them. In Malawi, the best-fit model to explain fruit consumption did not include any forest configuration metric, but it did include percentage forest cover.

We also examined how many days a week fruits were consumed (Tables 1 and S5). Greater forest cover meant that fruit was consumed on a greater number of days over the past week for households already consuming fruits, but only in Ethiopia ( $P < 0.05$ ) and Malawi ( $P < 0.01$ ). Moreover, the effect was small: the number of days with fruit consumption increased by 1.2% for each additional percentage of forest cover (Table S6). Again, the best-fit models did not include any configuration metrics.

To better understand the types of landscapes that support fruit consumption, we looked more closely at Ethiopia, Tanzania, and Uganda in which both forest cover and the number of forest patches were significantly associated with fruit consumption. We plotted the predicted probability of consuming fruits from our model against forest cover and the number of forest patches quintiles (Fig. 4), and several patterns emerged. Importantly, the marginal value of the predicted probability of consuming fruits within the past 7 days decreased in most cases as the number of forest patches or percent forest cover increased. For example, the mean predicted probability of consuming fruits in Tanzania increased by a factor 1.5 from the first to the second quintile of forest patches, whereas the marginal increase was reduced to a factor 1.2, 1.0, and 0.97 when comparing the second to the third, the third to the fourth, and the fourth to the fifth quintile, respectively.

<sup>1</sup> Data for Malawi shows lower consumption of dark green leafy vegetables than other studies that used different methodology and age groups, e.g. Kuchenbecker et al. (2017).

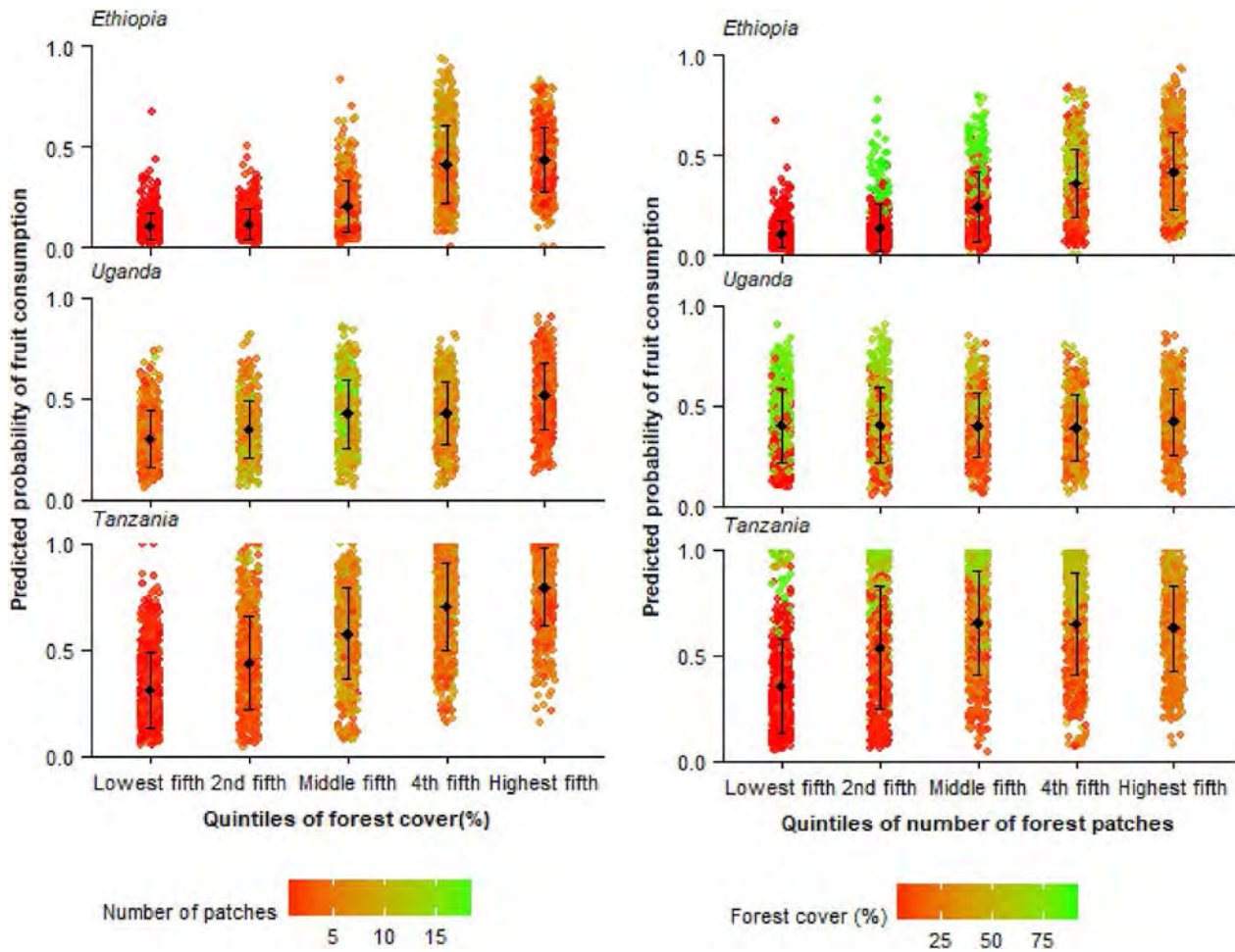




**Fig. 2.** Household consumption of the 10 food groups used to calculate the Modified Household Diet Diversity Score (MHHDDS) at different levels of the score. The 10 food groups are: 1) starchy staple foods (cereals, white roots, tubers, plantains), 2) other vegetables, 3) flesh foods, 4) other vitamin A-rich vegetables and fruits, 5) pulses (beans and peas), 6) nuts and seeds, 7) dairy, 8) eggs, 9) dark green leafy vegetables, and 10) other fruits. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Response variables	Forest configuration					Forest cover				
	Ethiopia	Uganda	Nigeria	Tanzania	Malawi	Ethiopia	Uganda	Nigeria	Tanzania	Malawi
Modified Household Diet Diversity Score (1-10)	# Patches ↗	# Patches ↗	# Patches ↗	NS	NS	↗	↗	NS	↘	↘
Probability of 'all fruit' consumption (yes/no)	# Patches ↗	# Patches ↗	# Patches ↗	# Patches ↗	NS	↗	↗	NS	↗	↗
Days with 'all fruit' consumption per week	NS		NS	NS	NS	↗		NS	NS	↗
Probability of mango consumption (yes/no)	NS	NS	NS	NS	NS	NS	↗	↘	NS	NS
Probability of 'wild fruit' consumption (yes/no)					Edge ↘					NS
Quantity of 'wild fruit' consumption (grams)					Patch size ↗					NS

**Fig. 3.** Effects of the proportion and spatial arrangement (configuration) of forest in a given landscape on multiple metrics of diets, holding all else constant. Five different configuration metrics were individually tested for significance in the models alongside forest cover: only the best performing model is shown. Green arrow: significant positive linear association; Green curve: significant positive quadratic association; Red arrow: significant negative linear association; Red curve: significant negative quadratic association; NS: non-significant. Data on days with fruit consumption were not available for Uganda, and the probability and quantity of 'wild fruit' consumption were estimated only in Malawi due to data availability. N(households): Ethiopia = 2635, Uganda = 2081, Nigeria = 1886, Tanzania = 2975, Malawi = 10,037. Regression results are presented in Tables S3–8. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)



**Fig. 4.** Relationships between forest cover and configuration and rural households' probability of consuming fruit. The predicted probability of consuming fruits is based on regression models (Table S5). Results are only shown for countries where both the percentage forest cover and the number of forest patches are positively and significantly associated with fruit consumption.

### 3.2. Relationship between forests and wild and domesticated fruit consumption

Whereas the preceding analyses demonstrated how people living in forested landscapes with many forest patches were significantly more likely to consume fruits, the results also suggested that a more nuanced analysis of specific fruit items might uncover mechanisms driving these relationships. To probe more deeply into this, we estimated a series of additional regression analyses.

First, because the surveys in Malawi recorded wild fruit explicitly (as opposed to grouped with “other” uncommonly consumed fruits), we estimated the effects of forest cover and configuration on a) a binary consumption/no consumption of wild fruits classification and b) the quantity of wild fruits consumed. In the best-fit model, forest edge density was negatively associated with whether or not people consumed wild fruits in the first place ( $P < 0.01$ ). Average patch size significantly positively influenced the quantity of wild fruits consumed ( $P < 0.01$ ) (Table S7). An increase in the average patch size by 1 ha increased the quantity of wild fruits by 190 g/household/week until a peak at an average patch size of about 11 ha. Yet, less than 4% of the households lived in landscapes with average forest patch sizes above this value.

Second, rural households often have cultivated fruit trees, such as mango, growing on their land (High and Shackleton, 2000; Miller et al., 2016), which potentially could explain the results on fruit consumption (Table S5), as such tree patches might be counted as forest in our analysis. To test whether this was the case, we re-ran our analysis with the most widely consumed fruit that is produced by cultivated trees, mango, as our response variable. We found that the effect of forest configuration was insignificant in all cases, while the effect of forest cover was significant in only Uganda and Nigeria, albeit in opposite directions (Fig. 3 and Table S8). We interpret this as evidence that the main results are not generally driven by the consumption of mango. Potential reasons include that mangos often are produced both for sale and consumption and that the consumption is highly seasonal (Keding et al., 2017).

Response variables	Wealth groups										Crop diversity				
	Ethiopia		Uganda		Nigeria		Tanzania		Malawi		Ethiopia	Uganda	Nigeria	Tanzania	Malawi
	Bottom → Middle	Bottom → Top	Bottom → Middle	Bottom → Top	Bottom → Middle	Bottom → Top	Bottom → Middle	Bottom → Top	Bottom → Middle	Bottom → Top					
Modified Household Diet Diversity Score (1-10)	↗	↗	↗	↗	↗	↗	↗	↗	↗	↗	↗	↗	↗	↗	
Probability of 'all fruit' consumption (yes/no)	NS	↗	↗	↗	NS	↗	↗	↗	↗	↗	↗	NS	NS	NS	
Days with 'all fruit' consumption (1-7)	NS	NS			NS	NS	NS	NS	NS	NS	↗		↗	↗	
Probability of mango consumption (yes/no)	NS	NS	NS	↗	NS	NS	↗	↗	NS	↗	NS	NS	NS	↗	
Probability of 'wild fruit' consumption (yes/no)									NS	NS					
Quantity of 'wild fruit' consumption (grams)									NS	↗					

**Fig. 5.** Effects of wealth and the number of crops grown on diets, holding all else constant. Green arrow: positive significant association; NS: non-significant. Data on days with fruit consumption were not available for Uganda, and probability and quantity of wild fruit consumption were estimated only in Malawi due to data availability. N(households): Ethiopia = 2635, Uganda = 2081, Nigeria = 1886, Tanzania = 2975, Malawi = 10,037. Regression results are presented in [Tables S3–8](#). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

### 3.3. Wealth and higher crop diversity may not be enough to ensure fruit consumption

Although the primary goal of this paper is to investigate the relationship between forests and people's dietary quality, it is also important to assess how dietary quality was associated with a broader set of socio-economic and geographical variables. We observed similarities across countries in the estimated effects of two of the variables listed in [Table 1](#). First, across all countries, wealthier households had greatest MHHDDS ( $P < 0.01$ ) and poorer households had the lowest MHHDDS ( $P < 0.01$ ) ([Fig. 5](#) and [S3](#)). Comparing the magnitude of the estimated coefficients revealed that being in the middle or highest wealth group was associated with a higher MHHDDS by 6.7–14.1% and 14.1–28.7%, respectively, compared to being in the lowest wealth group. This effect was least pronounced in Nigeria and most pronounced in Tanzania.

Second, the number of crops cultivated was positively and significantly related to MHHDDS across all countries. The estimated increase in MHHDDS was between 0.6 and 2.2% for every additional crop, with the lowest effect in Uganda ( $P < 0.1$ ) and the highest in Tanzania ( $P < 0.01$ ). For an average household in Tanzania with ~2 crops cultivated and a MHHDDS of 5.8, it would be an increase of MHHDDS by 0.13 for every additional crop grown.

While household wealth and the number of crops cultivated appeared to consistently positively influence the MHHDDS, the influence of these factors was not as consistent for fruit consumption. For example, only in Malawi, Uganda, and Tanzania were households in the middle wealth group more likely to consume fruits within the past week as compared to those in the lowest wealth group ([Table S5](#)). Yet, households belonging to the highest wealth group were significantly more likely to consume fruits as compared to those in the lowest wealth group across all countries ( $P < 0.01$ ). Only in Ethiopia did the number of crops grown influence the odds of consuming fruits with an estimated increase of 9% for every additional crop grown ( $P < 0.01$ ).

These results are interesting as they suggest that while greater wealth and more crop diversification might be important for securing a diverse diet, these factors alone may not be enough to ensure consumption of fruits in the first place. Rather, access to forests appeared to have a separate, though minor, influence on household fruit consumption.

## 4. Discussion and conclusions

As previous scholarly work on the role of forest for improving dietary quality has focused solely on the extent of forest or forest change ([Galway et al., 2018](#); [Ickowitz et al., 2014](#); [Rasolofson et al., 2018](#)), this paper has sought to shed light on the relationships between the spatial arrangement of forests and diets. We lay out three key findings demonstrating that our results help to further understandings of the association between forests and people's dietary diversity.

First, our results showed that the influence of forest on dietary quality extends beyond the proportion of forest in the landscape. A few examples substantiate this point. After controlling for forest cover, the number of forest patches was positively associated with households' dietary diversity and fruit consumption in three and four out of five countries, respectively. In other words, we found empirical support for our hypothesis that people's dietary diversity and their likelihood of consuming fruits increased with greater forest cover and higher number of forest patches. Whereas the mechanisms underlying the relations between forest configuration and people's dietary diversity score and fruit consumption are hard to ascertain, a number of possible explanations exist. These include: a) forest-based pollinators increase the production of domestic fruits in nearby areas, meaning that many smaller blocks of forests might lead to more effective pollination ([Garibaldi et al., 2013](#)), b) households are more prone to collect wild foods, including fruits, in the forest when traversing landscapes with many smaller blocks of forest ([Hickey et al., 2016](#)), c) small forest fragments may be 'managed forests' where valuable fruit trees are consciously maintained ([Padoch and Pinedo-Vasquez, 1996](#)), d) community access may be restricted from larger blocks of forest that are managed for conservation ([Ickowitz et al., 2019](#)), and e) smaller fragmented patches fail to house diverse wild fruits, resulting in people purchasing more fruits.



Second, because the dataset we used recorded household food consumption at the food item level rather than the food group level, we were able to demonstrate how the spatial arrangement of forest, in addition to forest cover, may influence the consumption of wild vs cultivated fruits in Malawi. Specifically, we demonstrated that the amount of forest influenced the consumption of 'all fruit' whereas the consumption of 'wild fruit' was associated with the forest configuration. This suggests that processes other than wild fruit harvesting may drive the association we see between forests and fruit consumption. In the other four countries, processes other than direct harvesting (for consumption) from the forest may likewise drive the associations seen between forest configuration (and cover for Uganda, Tanzania and Ethiopia) and 'all fruit' consumption. The absence of a significant association between 'all fruit' consumption and forest cover in Nigeria and forest configuration in Malawi might also be related to the more widespread fruit consumption in these two countries – in other words, forest configuration and cover might be more important at lower levels of fruit consumption.

Third, our results demonstrated that while more diverse diets were consistently associated with greater wealth and the number of crops grown, higher crop diversity might do little to secure the consumption of a nutritionally important food group, namely fruit. Households growing one crop or many crops were not more or less likely to consume fruits, suggesting that fruit is obtained off-farm – either from forests or markets. However, our results show that a) better market access did not translate into higher probability of fruit consumption

(nor a higher dietary diversity) and b) households in the middle wealth group, with allegedly higher purchasing power, did not enjoy greater fruit consumption than poorer households in two out of five countries. Given the importance of fruit for diverse long term health outcomes (Siegel et al., 2014; WHO, 2005), our results challenge the widely held assumption that promoting market access and income earning opportunities is sufficient to improve diets (Sibhatu et al., 2015).

One might expect the mixed results observed across countries to be related to factors such as the season of the data collection or the number of food items included in the survey. For example, the lower MHHDDS in Ethiopia may be due to the fact that 96% of the surveys were conducted in the dry season (primarily January). However, other studies have also found Ethiopia to have low dietary diversity relative to other countries (Hirvonen et al., 2016) and data collection in the dry season in Nigeria did not appear to be associated with a lower MHHDDS. What is similar for Uganda, Ethiopia, and Tanzania (all countries with a significant association between 'all fruit' consumption and number of forest patches and forest cover) – and different from Malawi and Nigeria – is the lower number of food items included in the survey and the less widespread fruit consumption. Thus, it is pertinent for future research to use similar survey instruments across countries, ideally with more detailed data collection on the specific types of e.g. fruits consumed as well as the source of these fruits.

As increasing agricultural production affords substantial opportunities for income growth (Rasmussen et al., 2018), what can policy-makers do to improve diet quality in rural areas where markets for nutritious foods are dysfunctional? A key challenge is to turn increased attention toward diet quality in food, agriculture and forestry policies, as increased agricultural production clearly does not address the widespread problem of diet quality (Pinstrup-Andersen, 2013). Establishing a coordinated food security and nutrition agenda for the agricultural sector and forest sector is thus likely a prerequisite to making any substantial progress on this front (Ruel and Alderman, 2013). Another challenge concerns the knowledge gap on potential trade-offs between forest conservation, food production and securing high quality diets. The EAT-Lancet commission recently stated the need for a more than 100% increase in the global consumption of fruits (and nuts, vegetables, and legumes) (Willett et al., 2019), yet no attention is given to the role of forests in securing sufficient supply of these food groups. Our finding that forests matter for fruit consumption emphasizes the need for future research efforts to consider how forests can be conserved in landscapes, while paying specific attention to regional differences, to maximize the supply of these food groups. From a conservation perspective, larger forest patches are often considered important for conserving biodiversity (Mitchell et al., 2013; Phalan et al., 2011). Yet, from a perspective of diet quality and nutrition we suggest that the spatial arrangement, and type of forest must also be considered.

In summary, any effective food security and nutrition strategy for rural Africa will need to increase the productivity of the agricultural sector. However, yield increases alone are unlikely to improve dietary quality and associated health outcomes. A multi-pronged effort which explicitly maintains or increases access to forest alongside other initiatives to improve income opportunities, biofortification, diversified agricultural production, would not only be more sustainable in the long run, but also more effective at providing well-balanced nutritious diets.

#### **Declaration of competing interest**

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at [https:// doi.org/10.1016/j.gfs.2019.100331](https://doi.org/10.1016/j.gfs.2019.100331).

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