Social as much as environmental: the drivers of tree biomass in smallholder forest landscape restoration programmes

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Acknowledgements

This work was funded by the University of Edinburgh E3 NERC doctoral training partnership grant (NE/L002558/1); the International Institute for Environment and Development and the Elizabeth Sinclair Irvine Bequest and Centenary Agroforestry 89 Fund. We would also like to thank: the participating farmers and technicians in Mexico, Uganda and Mozambique; our field research assistants Nadia Merkel and Chadreque Gurumane; at AMBIO in Mexico, Elsa Bazan Esquivel, Sotero Quechulpa Montalvo, Nicolas Hernandez, Ruben Trujillo and Marcos Antonio Hernández Vázquez; at ECOTRUST in Uganda, Pauline Nantongo, Lydia Kuganyirwa and Sheila Katushabe; in Mozambique, Afonso Jornale Thole and Andrew Kingman; at the Plan Vivo Foundation in the UK, Chris Stephenson and Eva Schoof; for initial data support Galina Toteva and Sarah Carter; for sage advice Dr Ina Porras; for editing and moral support Caroline Bec. We also thank the anonymous reviewers for their valuable comments.

Abstract

A major challenge for forest landscape restoration initiatives is the lack of quantitative evidence on how social factors drive environmental outcomes. Here we conduct a transdisciplinary quantitative analysis of the environmental and social drivers of tree biomass accumulation across 639 smallholder farms restoring native tree species in Mexico, Uganda and Mozambique. We use environmental and social data to assess the relative effects of key hypothesised drivers on aboveground biomass at the farm-level over ten years. We supplement this with a qualitative analysis of perspectives from local farmers and agroforestry technicians on the potential causal mechanisms of the observed social effects. We find that the material wellbeing of farmers (e.g. assets) and access to agroforestry knowledge explain as much variation in biomass as water availability. Local perspectives suggest that this is caused by the higher adaptive capacity of some farmers and their associated ability to respond to social-ecological shocks and stresses. Additionally, the variation in biomass between farms increased over time. Local perspectives suggested that this was caused by emergent exogenous and stochastic influences which cannot be reliably predicted in technical analyses and guidance. To deal with this persistent uncertainty, local perspectives emphasised the need for flexible and adaptive processes at the farm- and village-levels. The consistency of these findings across three countries suggests these findings are relevant to similar forest restoration interventions. Our findings provide novel quantitative evidence of a social-ecological pathway where the adaptive capacity of local land users can improve ecological processes. Our findings emphasize the need for forest restoration programmes to prioritise investment in the capabilities of local land users, and to ensure that rules support, rather than hinder, adaptive management.

Introduction

Forest landscape restoration (FLR) initiatives are at the forefront of efforts to reverse environmental degradation in terrestrial ecosystems (Chazdon et al., 2017). The success of FLR initiatives, however, has so far has been mixed (J. Aronson & Alexander, 2013; Mansourian et al., 2017).

A major challenge for restoration and other land management schemes is the difficulty of predicting, controlling and managing the outcomes of interventions in what are often highly complex and variable social-ecological systems (Messier et al., 2015). There is ongoing debate on the drivers of FLR outcomes, with different perspectives giving varying levels of emphasis to environmental and social factors. Some emphasise biophysical aspects and the need to build and support the integrity of ecological communities—there may be social benefits, but objectives can be primarily ecological, knowledge is technical, and minimising human intervention is seen as key (J. C. Aronson et al., 2018; Brudvig et al., 2017; Higgs et al., 2018; Suding et al., 2015; Temperton et al., 2019). Others emphasise the importance of institutional and social contexts that support good governance and adaptive management for sustainable and socially beneficial restoration (Mansourian, 2016; Van Oosten, 2013b). This divergence of perspectives on the drivers of environmental outcomes also extends to the related fields of conservation and payments for ecosystem services (Ezzine-de-Blas et al., 2016; Naeem et al., 2015; Pascual et al., 2014; Soule, 2013). Effective interdisciplinary approaches to FLR and similar interventions remain rare (Huber-Stearns et al., 2017; Mansourian et al., 2017).

One of the key gaps in interdisciplinary FLR remains the quantification of social drivers alongside environmental factors, and clear knowledge on the causality of social factors (Chazdon et al., 2017; Wortley et al., 2013). While the field of restoration ecology has generated a wealth of quantitative empirical research on the environmental aspects of restoration (Perring et al., 2015), due to the difficulty of measuring social phenomena, quantitative contributions testing theories from social science have remained rare (Geist & Galatowitsch, 1999; Kibler et al., 2018; Le et al., 2012; Miller & Hobbs, 2007; Sapkota et al., 2018). A consequence is that models and guidance for predicting and managing FLR outcomes are often focused on technical, largely environmental, factors (Wortley et al., 2013). On the other hand, in implementation, land management schemes are challenged to contend with a much broader array of both social and environmental factors (Van Oosten, 2013). Generating quantitative evidence on the relative importance and causal mechanisms of social factors remains a research frontier for FLR and other land management interventions (Chazdon et al., 2017).

Here we begin to address this gap through a novel interdisciplinary quantitative analysis of environmental and social drivers of tree biomass accumulation across 639 smallholder agroforestry farms restoring native tree species in projects in Mexico, Uganda and Mozambique. To our knowledge this is the first such quantitative analysis of its kind. Additionally, as we will elaborate, the consistency of our results across three countries strengthens the generalisability of our findings to similar land management interventions.

Agroforestry with native species is increasingly advocated as a key method of FLR, where farmers can increase native tree cover while maintaining crop production in agricultural landscapes (Erdmann, 2005; Robiglio & Reyes, 2016; Schroth et al., 2011). Smallholders are estimated to manage approximately 75% of the world's agricultural land (Lowder et al., 2016), and to make up most of the world's poor (Morton, 2007). Thus, many FLR initiatives, and particularly those in developing countries, will engage smallholders—and native-species agroforestry offers a key way to do this.

We focus on five key environmental and social factors theorised (by both experts and local land users) to drive biomass outcomes in such interventions: water availability; soil quality; existing tree cover at time of planting; household wealth and living standards (henceforth 'material wellbeing'; White, 2010); and household access to agroforestry knowledge. The environmental variables cover the key ecological considerations in designing agroforestry systems: sufficient water and soil nutrients are fundamental for tree growth, while tree cover at the time of planting serves as a proxy for inter-plant competition (Ashton & Montagnini, 1999; Corona-Núñez et al., 2018).

For social drivers, dimensions of household material wellbeing have been shown to be key factors in determining smallholder land management and resource use—people with different levels of deprivation have different capacities to manage land, and rely on different resources (Nahuelhual et al., 2018; Pritchard et al., 2018; Tittonell et al., 2005). For access to agroforestry knowledge, both vertical (expert to farmer) and horizontal (farmer to farmer) extension services (Altieri & Toledo, 2011) have been associated with the successful uptake of new land management techniques amongst smallholders (Baird et al., 2016; Clark et al., 2011).

More broadly, access to assets and knowledge are theorised to be central to the adaptive capacity, and associated resilience, of actors in natural resource management—a key factor underpinning the achievement of land management objectives despite emergent shocks and stressors (Thiault et al., 2019). For FLR, social factors, extension services and associated adaptive capacity are postulated to be key enabling factors for successful outcomes (Chazdon et al., 2017; Yin et al., 2013).

Our research questions are: which of the hypothesised environmental and social drivers have had the greatest effect on the AGB of trees established on agroforestry restoration farms? What are the causal mechanisms of the social effects? What are the implications for smallholder agroforestry, and other, FLR projects?

Methods

Study design

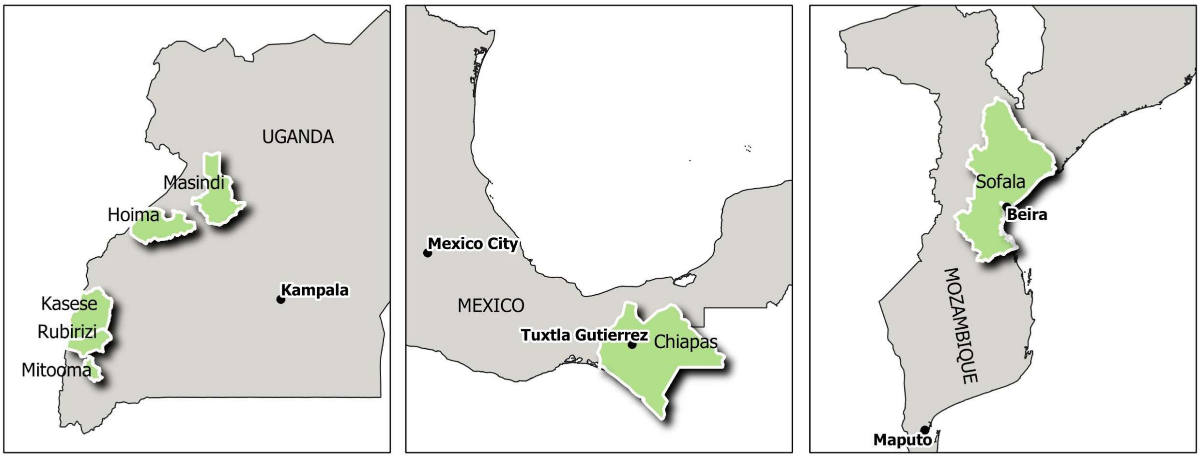
We use tree inventories, social surveys, spatiotemporal biophysical datasets, biomass modelling and mixed effects models to assess the relative effects of a set of hypothesised environmental and social drivers on the accumulation of aboveground biomass (AGB) at the farm-level across all three projects. We focus on AGB as a key metric for understanding changes in forest landscapes (Goetz et al., 2015). We identified the hypothesised drivers with reference to both the literature, and interviews with local farmers and agroforestry technicians. We also used these interviews to supplement the quantitative analysis with local perspectives on the potential causal mechanisms of the observed social effects.

Study areas

Our study sites cover farms participating in three smallholder agroforestry schemes: Scolel'te in Chiapas State in southern Mexico; Trees for Global Benefits in the districts of Rubrizi, Mitooma, Kasese, Hoima and Masindi in western Uganda; and the Sofala Community Carbon Programme in Sofala Province in central Mozambique (Figure 1). The farms in Mexico occur across a 240 km section of the highlands in Chiapas, along an ecological gradient from montane tropical rainforests to subtropical pine-oak rainforests (De Jong et al., 1995, p. 99). Farmers are from a diverse range of villages, spanning five culturally distinct *Maya* linguistic groups, and *mestizo* farmers of mixed descent (Ruiz-De-Oña-Plaza et al., 2011). In Uganda, sites occur along a 330 km section of the Albertine Rift characterised by crater lakes and tropical high forests. Farmers are members of a range of different *Bantu* linguistic groups (ECOTRUST, 2018). In Mozambique, sites are spread across a 30 km area of tropical open miombo woodland (sometimes classified as savannah) bordering the Gorongosa National Park (Ryan et al., 2011; Woollen et al., 2012). Farmers generally share *Sena* as their local language and are comprised of both long term residents and refugees who have settled in the 1990s following the Mozambican civil war (Hegde et al., 2015).

While socio-ecologically diverse, all can be categorised as remote areas dominated by subsistence agriculture and/or livestock systems, with high levels of poverty by global and national standards (OPHI, 2015, 2018a, 2018b). Additionally, all three schemes are funded by a mix of donor funds and carbon credits generated under the Plan Vivo Carbon Certification system (Plan Vivo, 2013). They thus have similar organisational processes and land management objectives, where a local organisation employs local technicians to help farmers to restore native tree species, and to monitor tree growth for 10 years after planting. These project processes are integrated with existing village institutions to varying degrees.

Figure 1. Maps of the regions covered in the study.



Sampling

We analysed a random sample of 639 households and their associated agroforestry farms (259 in Mexico, 321 in Uganda and 59 in Mozambique). In Mexico and Mozambique, we excluded farms for which we had insufficient social variables. Assessments of missing values showed no structure to the missingness, implying values were missing at random—

and thus that our overall sample can continue to be considered random (Kowarik & Templ, 2016). Our sampling frame covers populations of farmers who opted to participate in FLR in three different countries. We therefore interpret our results as case studies having relevance to similar interventions (Yin 2014).

Data: relative aboveground biomass

To generate farm-level estimates of AGB per hectare, we used farm-level tree inventories, the pantropical allometric models provided by Chave et al. (2009, 2014); and the BIOMASS package in R (Rejou-Mechain et al., 2018). We used Monte Carlo simulation to generate 95% credibility intervals (CI) of AGB on each farm. Each project implemented different styles of agroforestry with different expected rates. To enable comparisons of performance between agroforestry styles and plots of different ages we calculated a measure of relative aboveground biomass (RAGB). First, we used chronosequences (Walker et al., 2010) and least square log-linear regressions (Paine et al., 2012) to find the expected 'average' AGB per hectare for a particular year (up to 10 years since planting) for a given agroforestry style. We then extracted for each farm the adjusted standardised pearson residuals (i.e. the deviation of the farm AGB from the expected AGB, in standard error units; similar to a z-score) as an indicator of relative performance (Sorice et al. 2014; Kastenholz et al. 2007; Maschinski et al. 1997). We used the conservative RAGB value for each farm (the lower 95% CI RAGB for farms with mean RAGB > 0, and the upper 95% RAGB for farms with mean RAGB < 0, where RAGB $= 0$ indicates average performance).

Data: environmental explanatory variables

For water availability, we modelled the mean annual climatic water deficit (CWD) since planting on each farm (for a similar approach see Poorter et al. 2016) using farm location data, spatio-temporal records of temperature and rainfall from Willmot et al. (2014), digital elevation models (INEGI, 2018; USGS, 2006) and the CWD R function from Redmond (2015). For soil quality, we used estimates of cation exchange capacity (CEC) from the ISRIC SoilGrids spatial datasets (Hengl et al. 2017). For existing tree cover, we used farm locations and assessments of tree cover from Landsat and MODIS remote sensing data (Sexton et al., 2013) to estimate the proportion of tree cover on the plot in the year of planting.

Data: social explanatory variables

For material wellbeing, we constructed an index of multi-dimensional material wellbeing, using similar indicators and the same 'counting' approach as the widely-used global multidimensional poverty indicator (MPI; see Alkire & Jahan, 2018). We followed a similar approach to construct an index of access to extension services based indicators identified from local consultations and the existing literature (Altieri & Toledo, 2011; Birner et al., 2009; Krishna, 2004). See the Supplementary Material for further details on the social explanatory variables.

Table 2. Descriptive statistics of variables. Variables in bold are included in the main model.

	Mexico		Mozambique		Uganda	
Variable	**n**	**Mean ± SD (% for binary)**	**n**	**Mean ± SD (% for binary)**	**n**	**Mean ± SD (% for binary)**
Travel time to city (mins)	259	154.45 ± 84.18	59	225.42 ± 16.75	321	71.01 ± 23.68
Amount land (ha)	259	9.38 ± 6.74	59	1.51 ± 1.45	321	10.76 ± 14.67
Literacy	259	93%	59	44%	321	74%
Valuable assets (2nd model only)	259	52%	59	12%	83	29%
Above primary schooling 2nd model only)	259	53%	59	17%	60	25%
Employment contract (2nd model only)	106	8%	59	15%	85	11%
Formal land tenure	259	80%	59	51%	321	24%
People in household	259	4.27 ± 1.4	59	6.22 ± 1.92	321	8.71 ± 0.88
Wellbeing index (main model: simpler, full sample)	**259**	**3.93 ± 1.91**	**59**	**2.29 ± 0.89**	**321**	**1.99 ± 1.01**
Wellbeing index (2nd model only: broader, partial sample)	106	5.06 ± 2.13	59	2.73 ± 1.16	60	1.68 ± 1.13
Village AF experience (years)	259	4.61 ± 2.8	59	2.54 ± 2.28	321	2.5 ± 2.3
Technician in village	259	85%	59	36%	321	70%
Extension services index	**259**	**1.27 ± 0.47**	**59**	**0.59 ± 0.56**	**321**	**0.93 ± 0.55**
Tree cover at planting (%/ha)	**259**	**42.59 ± 13.06**	**59**	**10.04 ± 3.18**	**321**	**7.87 ± 2.36**
Cation exchange capacity (cmol+/kg)	**259**	**25.92 ± 3.54**	**59**	**9.38 ± 0.87**	**321**	**15.79 ± 3.49**
Mean climatic water deficit (mm/yr)	**259**	**-296.35 ± 139.11**	**59**	**-399.15 ± 119.75**	**321**	**-294.7 ± 128.5**
Relative aboveground biomass	**259**	**0.01 ± 0.74**	**59**	**0 ± 0.57**	**321**	**0.01 ± 0.79**

Data: local perspectives on social causality

To better frame our hypotheses, and to understand how social drivers operate, we conducted semi-structured interviews with 39 farmers and 23 technicians during field visits to Mexico, Uganda and Mozambique. We used a purposive sample to speak to farmers with varying levels of AGB performance and the main technicians associated with those farms. We conducted these interviews as broad, semi-structured conversations about the respondent's experience throughout the project, including open questions on why some farmers have bigger or different trees compared to others. Interviews were conducted with prior informed consent and anonymity was maintained throughout. We documented interviews in notes and audio recordings, sometimes with the assistance of translators fluent in the local languages.

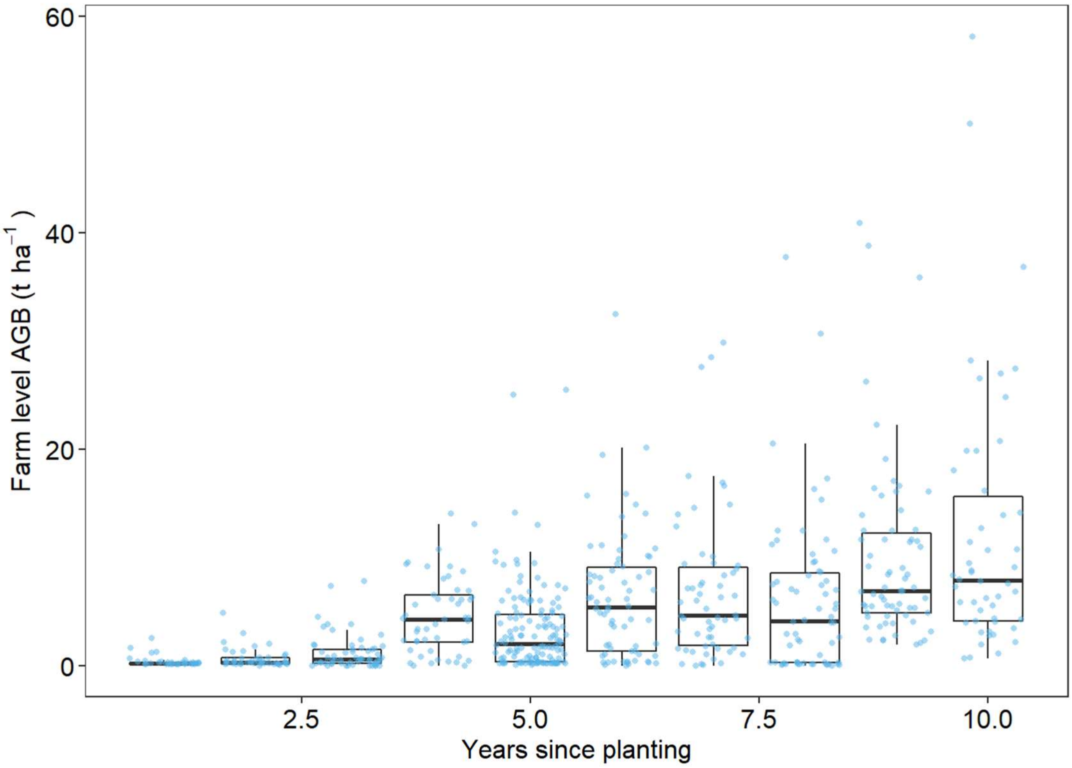
Analysis

For the quantitative analysis, we used linear mixed models with REML estimation and village as a random effect (minimum of 12 households per village). Diagnostics indicated a suitable fit with normally distributed residuals, homogenous variance and no significant collinearity among independent variables (see Supplementary Material for details; Zuur et al., 2007). We also subsequently conducted a likelihood ratio test to check the significance of the random effect of village (Kuznetsova et al., 2017), and assessments of spatial autocorrelation of RAGB in Mexico and Uganda using Moran's I (Mozambique had an insufficient sample for a robust test of spatial autocorrelation; Bivand et al., 2013; Overmars et al., 2003). All analyses were performed in R, version 3.5.1 (R Core Team, 2019), and the model code and diagnostics are in the Supplementary Material. For the qualitative analysis, we used thematic analysis (Ritchie et al. 2013) to frame the hypotheses around material wellbeing and agroforestry knowledge and, following the quantitative analysis, to examine in more depth the possible causal mechanisms behind the observed social effects. We include illustrative (anonymised) quotes from respondents in the results.

Results

Across our sites, farm-level AGB varied greatly, and this variation increased over time (Figure 2).

Figure 2. Boxplots showing variation in aboveground biomass between farms of different ages. The boxplots show quantiles, while the points are individual farms (horizontally jittered to the width of the boxplot). Tree stocking densities are a main determinant of AGB per ha, and target stocking densities varied between the different agroforestry styles included in the study. Here we show farm-level AGB for all land uses, normalised to a stocking density of 100 stems per ha.



Perspectives from farmers and local technicians suggested that this reflects the great and inherent social-ecological diversity amongst smallholdings, even across small areas (Box 1).

Box 1. Local perspectives on social-ecological diversity

Every farm is different. The soil changes from one farm to the other. Some are closer to the [existing rainforest] so they get more vines and shade. People also want to do different things on their farms.

Farmer, Mexico

People are not the same, so having one [agroforestry] plan does not work. You need several options with some flexibility. Some people like different trees because of the fruit or medicines. Also some trees grow better in some places but we don't really understand why. Even the [forest ecologists] don't know.

Agroforestry technician, Uganda

Local actors also suggested that following the establishment (tree planting) phase, land managers will lose control over outcomes as emergent social-ecological factors outside of their influence come to bear (Box 2).

Box 2. Local perspectives on a loss of control over emergent social-ecological factors

There have been big social and environmental changes since the beginning of the project. In some places there were floods, and in other years there were small fires. Other years it was ok. Also there are now more people and less land. [The project processes] had to change but you can't control everything.

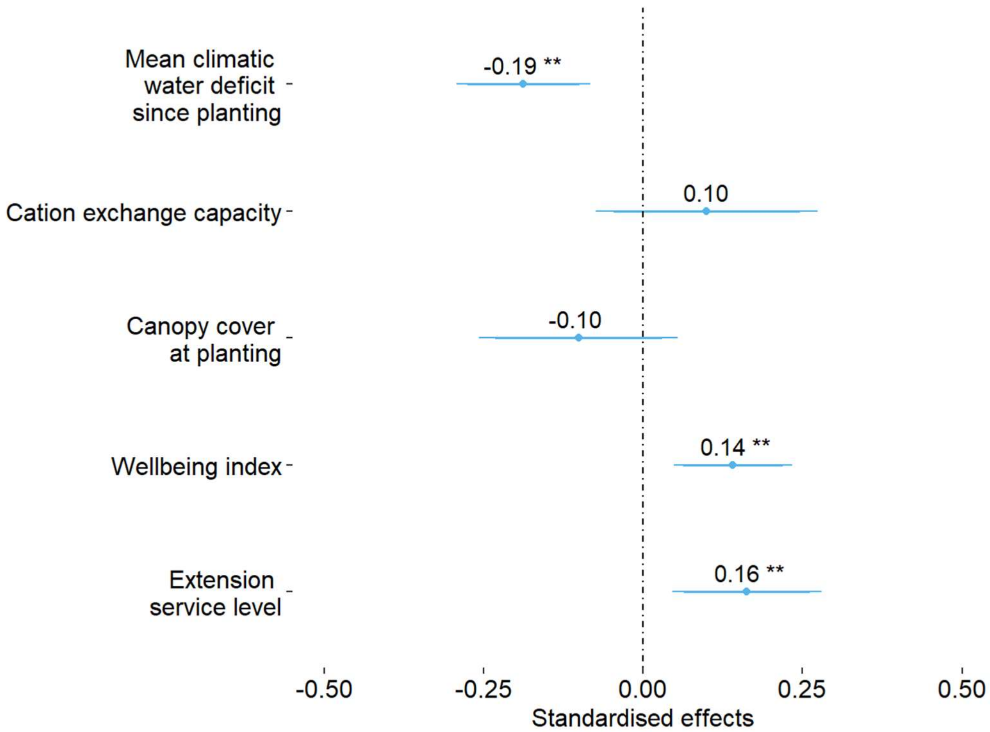
Agroforestry technician, Mexico

It was easy [to grow trees] at first, but then some [farms] do better than others. We had a dry year, so people that had just then planted now have smaller trees. Some people did a better job at watering [the saplings], but even then that didn't always work.

Farmer, Mozambique

In the regression analysis, the social factors of household material wellbeing and access to extension services each explained similar amounts of variation in RAGB to that explained by climatic water deficit (Figure 3). Cation exchange capacity and tree cover had no significant effects. For environmental effects, this indicates that all of our study sites may be broadly water (rather than nutrient) limited, and that existing tree cover has no consistent effect across sites (e.g. rather than limiting growth through inter-plant competition, for some species existing tree cover may create a favourable microclimate and the diffuse insolation that assists some saplings) (Ashton & Montagnini, 1999). Social factors appear as important for biomass accumulation as water availability. Given that variability in AGB increases over time and that we only model growth in the first ten years since planting, effects are likely to be greater by the time trees reach maturity (25 to 40 years).

Figure 3. Effects of hypothesised drivers on relative aboveground biomass.
Standardised estimates with 95% confidence intervals. * = significant with 95% confidence



The inclusion of village as a random effect significantly improved the model fit (X^2 = 46.77, df = 1, N = 639, p < 0.01), indicating that farms associated with the same village performed similarly. Conversely, however, there was low spatial auto-correlation of RAGB in Mexico (Moran's I = 0.23, p < 0.01) and Uganda (Moran's I = 0.14, p = 0.02) (Mozambique had an insufficient sample for a robust assessment). These results combine to indicate that there are additional drivers operating at the village level and that they are not strongly spatial. Assuming that environmental drivers are generally spatially correlated across larger scales (Dupuy et al., 2012; López-Martínez et al., 2013), these village-level drivers can be assumed to be social. In summary, the quantitative results indicate that the social drivers of material wellbeing and extensions services affect AGB accumulation as much as environmental factors, and these operate at both the household and village levels.

These statistical associations correspond with the consistent perspective amongst farmers and technicians that farmers with greater individual capabilities, and more supportive village institutions, were better able to innovate and adapt their land management in response to changing social and environmental conditions. Essentially, farmers with sufficient capabilities appear more able to overcome environmental barriers to tree growth (Box 3).

Box 3. Local perspectives linking social factors, adaptive capacity and tree growth

It is easier for richer people, or people with a bigger group to help, because they have more labour … and money is also important. When things happen, you can use the money to deal with it.

Farmer, Mexico

It was difficult because it was hard to do something new. Some of the trees didn't work because of the drought, then my husband got sick and it was difficult to fix things

Farmer, Mozambique

It was always harder when there is no one else doing agroforestry in the village. Farmers need to learn what works and this is always easier in a group, or when someone has done it already.

Agroforestry technicians, Uganda

I lived next door to the house where the [agroforestry technicians] would stay. It helped to have them next door. They would always come and give advice which helped the trees.

Farmer, Mozambique

More broadly, while our modelling showed some significant effects, most of the variation in AGB remained unexplained, despite the fact that we had accounted for (to the best of our ability) the major drivers suggested by local stakeholders and the technical literature. Combined with local perspectives on the inherent variability and dynamism of the social-ecological system (Box 1), this suggests that there are no simple explanations for variation in land management outcomes in our systems – drivers are likely diverse and very hard to measure and predict. In this context of continued uncertainty, local perspectives emphasised the importance of adaptive learning at the project, village and farm levels. As an agroforestry technician in Uganda told us: “New things arrive in the project that you cannot anticipate. So we need to be flexible if we can, while still caring for the trees and forest. When changes come, we all change as one.”

Discussion

In this study, we find strong quantitative evidence that the material wellbeing and knowledge of farmers can drive biomass accumulation as much as environmental factors in smallholder agroforestry FLR interventions. To the best of our knowledge, this phenomenon has not previously been demonstrated quantitatively. Additionally, the quantitative evidence suggests that these social factors operate at both the village and household levels.

Local perspectives emphasised that the broad causal mechanism for these social effects was that farmers with more resources and knowledge, and better support from village institutions, were better able to adapt their land use to emergent social-ecological shocks and stresses. This reaffirms existing theories on the importance of adaptive capacity for land management programmes (Thiault et al., 2019).

Our findings apply across sites in three countries. Given the need for FLR and other restoration programmes to engage rural smallholders in developing countries, we contend that our results are of relevance to the broader restoration field, and other land management interventions such as conservation and payments for ecosystem service schemes. Below we highlight two key contributions.

Social resilience and adaptive capacity drive restoration outcomes

A part of the restoration literature continues to view social factors and objectives as secondary (albeit admirable) considerations for restoration initiatives, relative to more important biophysical considerations (Aronson & Alexander, 2013; Higgs et al., 2018; Suding et al., 2015; Temperton et al., 2019). This view is also prominent in part of the associated conservation and payments for ecosystem services literatures, where social objectives are sometimes seen as aspirational but not integral (and sometimes as a distraction) to technical and biophysical factors (Ezzine-de-Blas et al., 2016; Naeem et al., 2015; Soule, 2013).

Our results provide robust empirical evidence demonstrating that the social situation of local resource users has a significant, tangible effect on biophysical restoration outcomes. This accords with existing literature on the importance of social factors supporting good governance (Mansourian, 2016; Van Oosten, 2013), and extends this to emphasise the importance of supporting the adaptive capacity of individual participants. While improvements in ecological processes are often theorised to benefit humans (Díaz et al., 2018), here we have clear evidence of a reciprocal pathway: in certain contexts improvements to human capabilities can benefit ecological processes. Essentially, the effectiveness of a land management intervention may only be as good as the social-economic resilience and adaptive capacity of its local participants. Restoration, and related conservation and payments for ecosystem services projects, should thus put such factors on par with biophysical and other technical considerations.

One interpretation of this finding could be that restoration and similar programmes should avoid engaging poorer people with low capabilities. However, where interventions are aiming for a socially beneficial and landscape-level transformation, excluding more vulnerable people is likely not an option. On the social side, interventions would need to consider the social impacts of excluding already vulnerable and marginalised people from natural resource management programmes, and the related risk of elite capture (Persha & Andersson, 2014). Excluding particular actors could also have knock on effects on community support for the project, and associated local perceptions of project legitimacy (Pascual et al., 2014). Regarding landscape-level transformation, excluding particular actors could restrict interventions to site-level rather than landscape-level interventions, which would likely not achieve the changes that many hope for (Chazdon et al., 2016; Lamb et al., 2005). It could also drive 'leakage' where conservation of one place in the landscape just moves degradation elsewhere (Bode et al., 2015). Programmes seeking socially beneficial, landscape-level change will thus likely need to engage many actors, including vulnerable people. Allocating resources and designing institutions to supporting the adaptive capacity and capabilities of local resource users will be key. This will be particularly important for engaging smallholders, who are often poorer and control much of the world's land (Lowder et al., 2016; Morton, 2007).

Accepting uncertainty and supporting adaptive management

A second key finding of our study is that great variability in land management outcomes may be the norm rather than the exception in smallholder FLR and similar projects, even amongst sites in similar areas with similar land use objectives. Further, this variability likely increases over time. Local perspectives suggest that, rather than technical staff and FLR administrators progressively refining their knowledge and management of the system to reduce variability in outcomes, such actors may in fact begin to lose influence over land management outcomes after the initial establishment of the system. After this, exogenous and stochastic influences may come to dominate, pushing the system beyond the predictive and managerial control of land analysts and users.

Alongside our findings about local adaptive capacity, this emphasises the need to moderate expectations of being able to accurately design and predict interventions and outcomes (Brudvig et al., 2017). Instead our evidence supports calls to invest in flexible rules and institutions that support rather than hinder adaptive management in restoration and related initiatives (Mansourian et al., 2017; Murray & Marmorek, 2003). Adaptive management is increasingly argued to be key for dealing with uncertainty and complexity in social-ecological systems (Schultz et al., 2015), and our quantitative and qualitative findings support such an approach. This speaks to an ongoing tension in the restoration and conservation literature between those who wish to standardise 'best practice' approaches, and those who wish to maintain flexibility (Aronson et al., 2018; Higgs et al., 2018; Wunder et al., 2018). We contend that all initial designs and predictions of restoration and other land management projects are likely to turn out to be at least a little inaccurate in practice—investing in adaptive project processes to adjust and correct interventions over time will therefore be key.

Conclusion

Our work offers novel evidence on the importance of social factors in driving outcomes in FLR and similar initiatives. We have shown across several hundred farms in three countries that the capability and knowledge of land users can drive outcomes as much as environmental factors—and that this is likely tied to the capacity of land users to respond and adapt to social-ecological shocks and stresses. While there are no doubt many other drivers of outcomes in our sites, and while the magnitude of the effects will likely vary across contexts, we argue that the consistency of our findings across three sites strengthens their relevance for other sites and programmes.

Broadly, we contend that restoration initiatives and similar land management programmes must build and maintain the adaptive capacity of smallholders and other local actors through both material and institutional support. Additionally, project designs, funding and rules must be flexible enough to support adaptive management in the context of continued uncertainty. Overall, we suggest that the field of 'restoration ecology' must become 'adaptive restoration social-ecology' if it is to succeed.

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Supplementary Material

Background

Below follows more detail on the construction of the material wellbeing index (Part 1), the extension services index (Part 2), and the model code and diagnostics (Part 3).

Part 1: Material wellbeing index

For material wellbeing, instead of relying on unidimensional monetary or asset-based approaches, we adopt the increasingly applied ‘capabilities’ approach to characterising levels of deprivation in dimensions of material wellbeing across different households and their agroforestry farm (Leach, Mearns, & Scoones, 1999; Sen, 1999; Alkire et al. 2014). Our aim was to generate a household-level indicator that was comparable across datasets, and which could be supported by the available data. We sourced our data from an existing social survey in our Mozambique site (Jindal et al., 2012) and project records on household social variables in Uganda and Mexico, supplemented by a new household survey in Mexico. The social data are summarised in Table S1.

Motivated by existing approaches for integrating such social information across different datasets (Alkire & Foster, 2011), we adopted an approach of counting the number of deprivations across different material wellbeing dimensions within a household, based on similar variables available across sites (Atkinson, 2003). This method originates from capability approaches to human welfare (Leach et al., 1999; Sen, 1999) and similar indicators have been used for analyses of deprivation across different sites and countries (Alkire et al., 2017; Feeny & McDonald, 2016; Smith et al., 2019).

To generate the indicators, guided by consultations with local participants and the literature on similar indicators globally (Alkire & Jahan, 2018; Alkire & Santos, 2014; Headey et al., 2018) and in our study countries (Battiston et al., 2013; Schreiner, 2013, 2015, 2017; Smith et al., 2019), we first identified suitable variables that were present across our sites. We focused on variables that were likely to indicate longer-term levels of deprivation rather than variables likely to fluctuate with small variations in cash income (Alkire et al., 2015). We identified eight variables relating to education and living standards dimensions (Table 1). We then applied to each variable a cutoff value (also based on the aforementioned literature and consultations) below which a household is assumed to be ‘deprived’ in that dimension. Where we could not identify a suitable cutoff value for continuous variables, we used the (within dataset) median as the cutoff to generate a relative measure of deprivation. Next, to form an aggregate indicator, we summed the number of dimensions in which a household is deprived (Atkinson, 2003; Smith et al., 2019). This provides an ordinal indicator on the likely level of deprivation (in education and living standards) faced by a household. Unlike poverty indices, we did not apply a second cutoff to this aggregate indicator to create a binary variable identifying those below a poverty threshold. Instead we retained the variable as a multi-level ordinal variable with more complete information on the difference in deprivation between households (Alkire & Foster, 2011), and termed it a material wellbeing index.

Table S1. Variables used in wellbeing indicator. Variables not in the full sample are only included in the wellbeing indicator for the secondary model (reported in Supplementary Material).

Dimension	Indicator	Deprived if… (cutoff value)	Source	In full sample
Education	Literacy	Speaks only the local language and/or cannot write in official language	Household surveys (Mexico and Mozambique); Project records (Uganda)	Yes
	Years of schooling	No household member has completed six years of schooling.	Household surveys	No
Living standards	Remoteness	Above median travel time from household to nearest town of 50,000 people	Weiss et al. 2018	Yes
	Land size	Below median amount of land available to household for agriculture.	Project records (Mexico and Uganda); Household survey (Mozambique)	Yes
	Formal employment	No one in the household has an employment contract	Household surveys	No
	Land title type	No formal land title approved by relevant authority	Project records	Yes
	Household size	Above median household size	Household surveys (Mexico and Mozambique); Project records (Uganda)	Yes
	Assets	The household owns more than one valuable asset (as defined in existing site- and/or national surveys)	Household surveys	No

Across the datasets there were large numbers of missing observations for variables relating to years of schooling, valuable assets and formal employment. Including these variables in the wellbeing indicator would thus reduce our sample from 639 to 225 households. In addition to reducing the power of our model, this would potentially bias our sampling frame towards households more likely to successfully report these variables. To balance the need for a breadth of material wellbeing indicators with the need to retain a sufficient and random sample, we thus ran two models: the main model with the original sample and a simpler five-variable material wellbeing index, excluding variables on years of schooling, valuable assets and formal employment (but retaining other measures on education and livelihoods); and a secondary model with a smaller sample and a broader eight-variable wellbeing index including all variables. In the results in the main paper, we present the results of the main model while the results of the secondary model are in Part 2 of the Supplementary Material below. The two alternative wellbeing indicators are very strongly correlated ($r(225) = 0.94$, $p < 0.01$), and the results for the second model are similar to those of the main model (but this second model is likely underpowered and the sampling frame uncertain).

Part 2: Extension services index

To generate a comparable measure of access to extension services across sites we used the same data sources and 'counting' approach as for the wellbeing index. Based on local consultations and literature (Altieri & Toledo, 2011; Birner et al., 2009; Krishna, 2004) we identified two commonly available variables on the provision of agroforestry knowledge in our sites: a) whether an agroforestry technician lives in the village; and b) the number of years that the agroforestry project has existed in the village prior to tree planting on a farm. We then applied cutoff values to assess if a household was deprived in any of these dimensions, respectively: a) no technician present; and b) below the median number of years within a site. Finally, we summed these scores to generate a three-level ordinal variable on the likely availability of extension knowledge for a household.

Part 3: Model code and diagnostics

Given the two wellbeing indices (see Part 1 above), we ran two mixed models: the main model with the full sample and simpler wellbeing indicator (reported in the main manuscript); and a second model with a partial sample and a broader wellbeing indicator (reported below). Both wellbeing indicators are highly correlated and the model results are very similar.

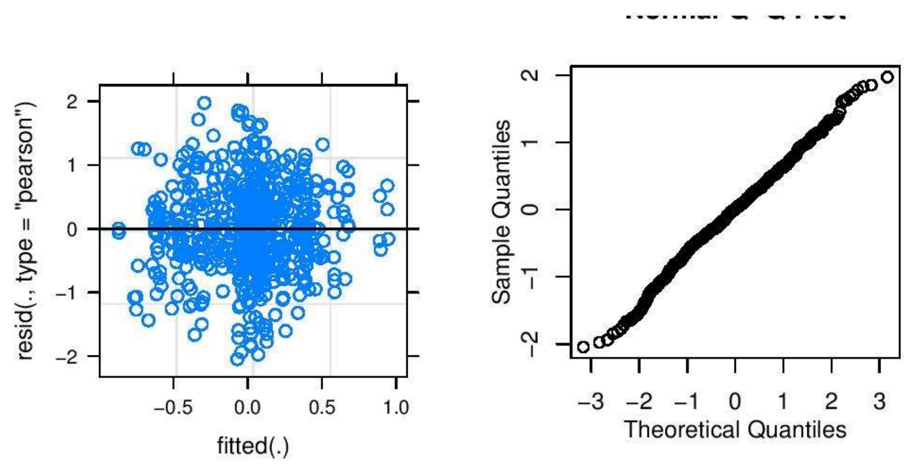
Below follows the R code for the two mixed models in the paper:

1. the main model which has the full sample and a simpler wellbeing indicator; and
2. the secondary model which has a partial sample and a broader wellbeing indicator.

1. Diagnostics and summary for main model

```
### a) RUN MIXED MODEL FOR ALL SITES, FULL SAMPLE
# 639 farms
lmm <- lme4::lmer(ragb ~ cvr + cwd + cec + wb_ind_ms +
                  ext + (1 | vl) , data = dat_all)

### b) CHECK MODEL FIT
p1 <- as.grob(plot(lmm,main="")) # residuals
p2 <- as.grob(function() qqnorm(resid(lmm))) # qqplot
grid.arrange(p1,p2,nrow=1)
```




```
#                  RESIDUALS                                    QQPLOT
# Residuals look ok.

### c) CHECK FOR MULTICOLLINEARITY
usdm::vif(dat_all[names(lmm@frame)[c(-1,-(ncol(lmm@frame)-1),-(ncol(lmm@frame)))]])
```

```
##   Variables      VIF
## 1       cvr 2.314785
## 2       cwd 1.247171
## 3       cec 2.244861
## 4 wb_ind_ms 1.428618
```

```r
# vif below threhsold of 4 so looks ok.

### d) MODEL SUMMARY
summary(lmm) # model
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: ragb ~ cvr + cwd + cec + wb_ind_ms + ext + (1 | vl)
##    Data: dat_all
##
## REML criterion at convergence: 1380.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.00662 -0.61231  0.01264  0.63176  2.90328
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  vl       (Intercept) 0.08225  0.2868
##  Residual             0.46256  0.6801
## Number of obs: 639, groups:  vl, 10
##
## Fixed effects:
##               Estimate Std. Error t value
## (Intercept) -0.7584340  0.2751449  -2.756
## cvr         -0.0040027  0.0031398  -1.275
## cwd         -0.0010372  0.0002945  -3.522
## cec          0.0111565  0.0099708   1.119
## wb_ind_ms    0.0618014  0.0208648   2.962
## ext          0.1962375  0.0720087   2.725
##
## Correlation of Fixed Effects:
##           (Intr) cvr    cwd    cec    wb_nd_
## cvr       -0.096
## cwd        0.622  0.158
## cec       -0.797 -0.090 -0.417
## wb_ind_ms -0.134 -0.120  0.016 -0.096
## ext        0.022 -0.123  0.045 -0.235  0.002
```

```r
# Result: water, extension and wellbeing all similarly important.
# Village is a significant predictor

### e) CHECK SIGNIFICANCE OF RANDOM EFFECT
lmerTest::rand(lmm)
```

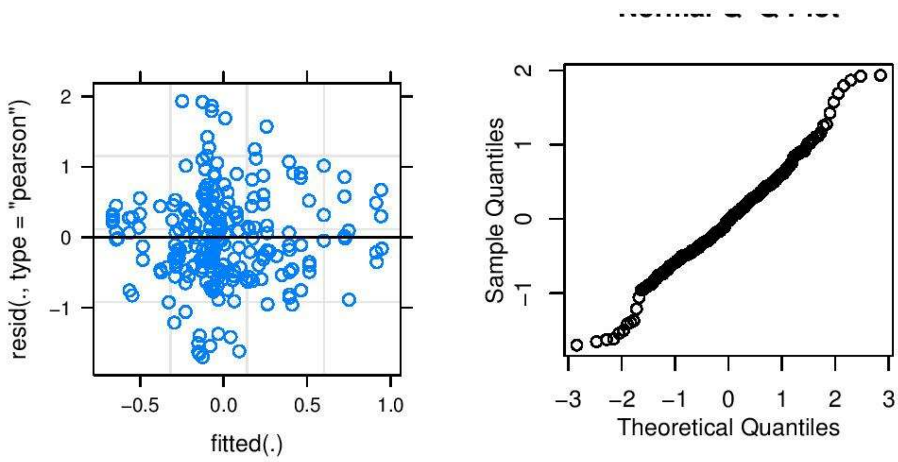
```
## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## ragb ~ cvr + cwd + cec + wb_ind_ms + ext + (1 | vl)
##          npar  logLik    AIC    LRT Df Pr(>Chisq)
## <none>      8 -690.43 1396.8
## (1 | vl)    7 -713.80 1441.6 46.756  1  8.041e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# keep model
p1_dat$md_all_ms <- lmm
```

2. Diagnostics and summary for secondary model

```r
### a) RUN MIXED MODEL FOR ALL SITES, PARTIAL SAMPLE TO MAXIMISE DIMENSIONS
# - 225 farms.
lmm <- lme4::lmer(ragb ~ cvr + cwd + cec + wb_ind_md +
                    ext + (1 | vl), data = dat_all)

### b) CHECK MODEL FIT
p1 <- as.grob(plot(lmm,main="")) # residuals
p2 <- as.grob(function() qqnorm(resid(lmm))) # qqplot
grid.arrange(p1,p2,nrow=1)
```




```r
#                  RESIDUALS                                           QQPLOT
# Residuals look ok.

### c) CHECK FOR MULTICOLLINEARITY
usdm::vif(dat_all[names(lmm@frame)[c(-1,-(ncol(lmm@frame)-1),-(ncol(lmm@frame)))]])
```

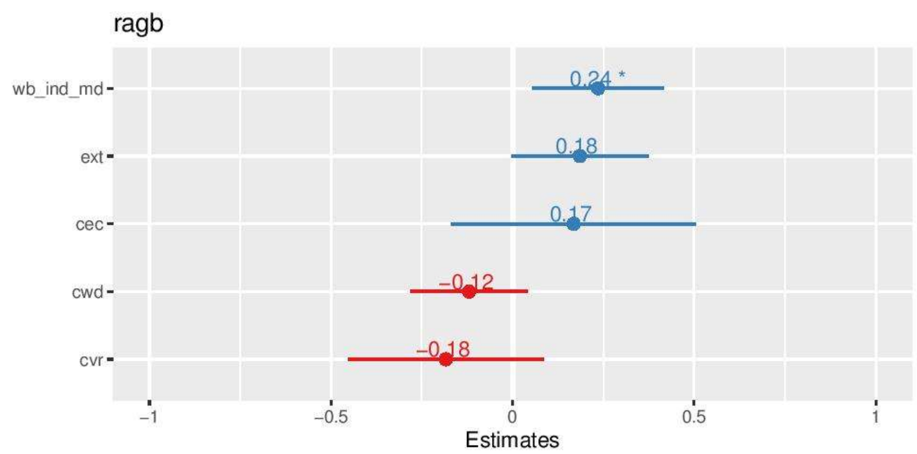
```
##   Variables      VIF
## 1       cvr 3.466714
## 2       cwd 1.608355
## 3       cec 3.607640
## 4 wb_ind_md 1.776097
```

```r
# vif below threhsold of 4 so looks ok.

### d) MODEL SUMMARY AND DOT WHISKER PLOT
summary(lmm) # model
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: ragb ~ cvr + cwd + cec + wb_ind_md + ext + (1 | vl)
##    Data: dat_all
##
## REML criterion at convergence: 512.6
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.48378 -0.62129 -0.02317  0.60756  2.82509
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  vl       (Intercept) 0.08173  0.2859
##  Residual             0.46763  0.6838
## Number of obs: 225, groups:  vl, 7
##
## Fixed effects:
##               Estimate Std. Error t value
## (Intercept) -0.8818015  0.3934069  -2.241
## cvr         -0.0071341  0.0053457  -1.335
## cwd         -0.0006739  0.0004640  -1.452
## cec          0.0168807  0.0172964   0.976
## wb_ind_md    0.0797312  0.0312720   2.550
## ext          0.2134070  0.1111786   1.919
##
## Correlation of Fixed Effects:
##           (Intr) cvr    cwd    cec    wb_nd_
## cvr        0.019
## cwd        0.542  0.218
## cec       -0.766 -0.324 -0.370
## wb_ind_md -0.046 -0.080  0.103 -0.256
## ext        0.104 -0.022  0.168 -0.374  0.103
```

```r
sjPlot::plot_model(lmm, "std", sort.est = TRUE,
           terms = names(lmm@frame)[-1],
           show.values = TRUE, show.p = TRUE)
```




```
# Result: similar to above. But model is likely underpowered and we no longer
# know if sample is random.

### e) check correlations of wellbeing variables in the two models
cor.test(dat_all$wb_ind_md,dat_all$wb_ind_ms)
```

```
##
##  Pearson's product-moment correlation
##
## data:  dat_all$wb_ind_md and dat_all$wb_ind_ms
## t = 40.21, df = 223, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.9193716 0.9515610
## sample estimates:
##       cor
## 0.9374396
```

```
# the two wellbeing variables are very highly correlated, so the results
# from the main model (with the simpler wellbeing indicator) are robust.

# keep model
p1_dat$md_all_md <- lmm
```

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