



Landscape and management influences on smallholder agroforestry yields show shifts during a climate shock

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ABSTRACT

Sustaining yields for smallholder perennial agriculture under a rapidly changing climate regime may require consideration of landscape features and on-farm management decisions in tandem. Optimising landscape and management may not be possible for maximising yields in any one year but maintaining heterogeneous landscapes could be an important climate adaptation strategy. In this study, we observed elevation, forest patch and shade management gradients affecting smallholder coffee (*Coffea arabica*) yields in a ‘normal’ year versus the 2015/16 El Niño. We generally found a benefit to yields from having leguminous shade trees and low canopy openness, while maintaining diverse shade or varying canopy openness had more complex influences during a climate shock. The two years of observed climate shock were dominated by either drought or high temperatures, with yield responses generally negative. Climate projections for East Africa predict more erratic rainfall and higher temperatures, which will disproportionately impact smallholder farmers.

1. Introduction

Mean global temperatures and the incidence of extreme climate shocks are increasing, including dangerously elevated temperatures during cyclical El Niño events in the tropics (Rifai et al., 2019). Smallholders can be particularly vulnerable to climate shocks as they have limited ability to shift their production across the landscape, often have insecure tenure and lack access to the most fertile land areas (Ribot and Peluso, 2003). The most food insecure farmers have been found to have the least capacity to adopt climate adaptation strategies, suggesting a very concerning feedback loop (Shikuku et al., 2017). Unfortunately, when compared to annual crops, comprehensive assessment of climate variability and ongoing climate change on perennial crops remains

relatively rare (Gunathilaka et al., 2018). This needs to be urgently addressed as adaptive management will require planning on the scale of years rather than growing seasons.

In addition, there is a risk the traditional focus on intensification of agriculture to maximise yields under “normal” conditions may result in greater vulnerability of farms to climate extremes (Lin et al., 2008). Often management decisions more focused on minimising variability or reducing recovery times in yields of perennial crops are reliant on enhanced ecological knowledge of a farm (Morel et al., 2019a; Tschardt et al., 2012; Wanger et al., 2020). Traditional smallholder systems often already use agroecological methods (Altieri and Nicholls, 2017), hence it is important for extension interventions to complement this knowledge. At the same time, changing climate conditions may pose

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challenges to relying solely on traditional farm management practices.

Agroforestry systems are relatively common in smallholder systems and are considered an effective strategy for achieving climate resilient agriculture (Vaast et al., 2016), particularly to temper the impacts of climate shocks for understory crops (Tschamtko et al., 2011). During dry season conditions, shade trees ameliorate temperature extremes; however, they may not be able to maintain optimal humidity levels to the same extent as during wet seasons (Blaser et al., 2018). For low-input smallholder systems, leguminous trees, or those with symbiotic relationships with N_2 -fixing microbes, are an important source of nutrients and have been planted as shade trees (Beer et al., 1998). However, the practice is limited due to costs (Vaast et al., 2016) and in some cases has caused mortality events during climate shocks by outcompeting understory crops for ground water (Abdulai et al., 2018).

With agronomic advice often focused on the farm-scale and intended to optimise management for previously experienced climatic conditions, there is an urgent need to capture and understand farm productivity dynamics at multiple spatial and temporal scales. Landscape-scale conditions such as the prominence of remnant forest and altitude have been found to influence micro-climates (Jucker et al., 2018), shading of crops (Schmidt et al., 2019), disease incidence (Garedew et al., 2020), pollinator abundance (Grass et al., 2018) and nutrient cycling (Jha et al., 2014). While these large-scale processes are out of the control of the smallholder farmer, on-farm management decisions may be able to compensate somewhat for landscape effects, including maintaining structural complexity of the farm (Garedew et al., 2020; Geeraert et al., 2019).

Extensive research has been done on the ecology of the perennial cash crop, *Coffea arabica*, and the agroecological practices that can be adopted to improve *C. arabica* productivity under agroforestry management (Perfecto et al., 2014). *C. arabica* is known to have low adaptive capacity to climate change (Davis et al., 2012). It is particularly sensitive to temperature, variability in rainfall and soil water availability (Camargo, 2010). Projected changes in climate are expected to reduce viability of *C. arabica* at lower elevations and potentially lead to forest clearance as new cultivated areas are established to meet growing demand (Bunn et al., 2015; Magrath and Ghazoul, 2015; Ovalle-Rivera et al., 2015). For Ethiopia, projections of *C. arabica* suitability depend on whether available areas for cultivation can migrate to higher elevations, which could displace existing agricultural activities (Moat et al., 2017). Pressures to intensify agriculture in the highlands of Ethiopia will be inevitable as the food security needs of Ethiopia's growing population are unlikely to be met by increasingly marginal lowland areas (Jury and Funk, 2012). Therefore, better understanding the adaptability of this perennial crop to changing climate conditions under current landscape configurations is needed.

In Ethiopia, coffee production is dominated by low-input, smallholder farmers, who largely manage their *C. arabica* shrubs through maintaining shade trees and some weeding. Often these farmers have little capacity to respond to sudden climate shocks, with spatial concentrations of climate vulnerability correlated with location in the landscape, migration status and access to roads (Morel et al., 2019b). Planting trees, changing crop management and adopting soil conservation practices are among the identified adaptive measures in Ethiopia; although a significant proportion of farmers reported not adopting any adaptive management strategies (Gbegbelegbe et al., 2018).

The aim of this study was to observe holistically the effect of management and landscape factors on *C. arabica* yields to identify which parameters were the most influential and whether these were under the control of the farmer. Due to the timing of the plot network establishment and the 2015/16 El Niño event, this study was also able to consider how these influences may vary under different climate conditions to explore the potential for optimal management and landscape location for enhancing climate resilience. The sampling design was across elevation, forest patchiness and shade management gradients in the UNESCO Yayu Coffee Forest Biosphere Reserve. Data was collected over

three years. We present a number of landscape and management influences on coffee shrub yield for “all years” together, the “normal” year we monitored and for the two “shock” years.

2. Results

Three-month rolling averages of normalised maximum temperature and water deficit anomalies for the time period 1980–2017 are presented (see Fig. 1a & 1c), with the study period highlighted with dashed lines, and zoomed into the 3 years of the monitoring period (see Fig. 1b & 1d). The figure includes shading using the Ocean Niño Index (ONI) estimated by NOAA (2019) based on the ERSST v5 analysis (Huang et al., 2017). From this figure, there does not appear to be a consistent influence of El Niño events on quarterly averaged water deficit anomalies from 1980 to the present; however, maximum temperature anomalies appear to correspond with strong El Niño events and show a consistent increase since 2000. Focusing on the study period (1b & 1d), it is evident that maximum temperatures were significantly higher, although the strongest impact began during the period of berry development in 2015 and then was elevated but less extreme throughout 2016. Averaged water deficits show differing patterns in the shock years during the local dry season (December to April), with consistently drier conditions in 2015 and a more mixed signal in 2016. Both years differ from 2014, where relatively minimal anomalies were observed.

2.1. Observed differences between normal and shock years

Median shrub yields showed a dramatic reduction over the study period, visible in the annual means and standard errors presented in Fig. 2. From this figure it is evident that not all farms exhibited the same response across the three years, with some showing a consistent drop in yields while others showed less severely impacted yields or yield recoveries in the first or second year of the climate shock. However, at the scale of the landscape annual median shrub yields consistently decreased from 2014 to 2016.

2.2. Yield models for normal and shock years

We developed one yield model for all years with year as a factor and plot as a random effect. We found only a few parameters were consistently statistically significant. Year was the strongest predictor of yield outcome with 2016 more negative ($p < 0.001$) than 2015 ($p < 0.001$) and elevation positive ($p < 0.05$) for yields (Fig. 3a). For the “all year” model, we found the maximum temperature anomaly to be highly correlated with year, therefore, it was removed for the final model. The most parsimonious model included coffee berry borer (negative, $p < 0.05$), leguminous shade trees (positive, $p < 0.1$), shade diversity (negative, NS), canopy gap (nonlinear, NS), soil carbon nitrogen ratio (negative, NS) and location within a forest patch (neutral, NS).

For our normal year of yield monitoring (2014), we found the most statistically significant parameters influencing shrub yield were elevation (positive, $p < 0.001$), diversity of shade trees (negative, $p < 0.01$), canopy gap above coffee shrubs (negative, $p < 0.05$), whether a farm was located within a forest patch (positive, $p < 0.1$) and soil potassium (positive, NS) (Fig. 3b). We also found an interaction between diverse shade and basal areas of leguminous trees to be statistically significant ($p < 0.05$).

We developed one yield model for both shock years (2015 & 2016) with plot as a random effect. Similar to the yield model for all years, only a few parameters were significant. Anomalies in maximum temperature during berry development (June to October) were the most influential parameter and was positive ($p < 0.01$). Coffee berry borer (negative, $p < 0.05$) was also significant. Landscape influences were less pronounced with patch area (negative, $p < 0.1$), elevation (positive, NS) and an interaction between the two parameters ($p < 0.1$). Shade tree influences remained in the final model, including leguminous trees

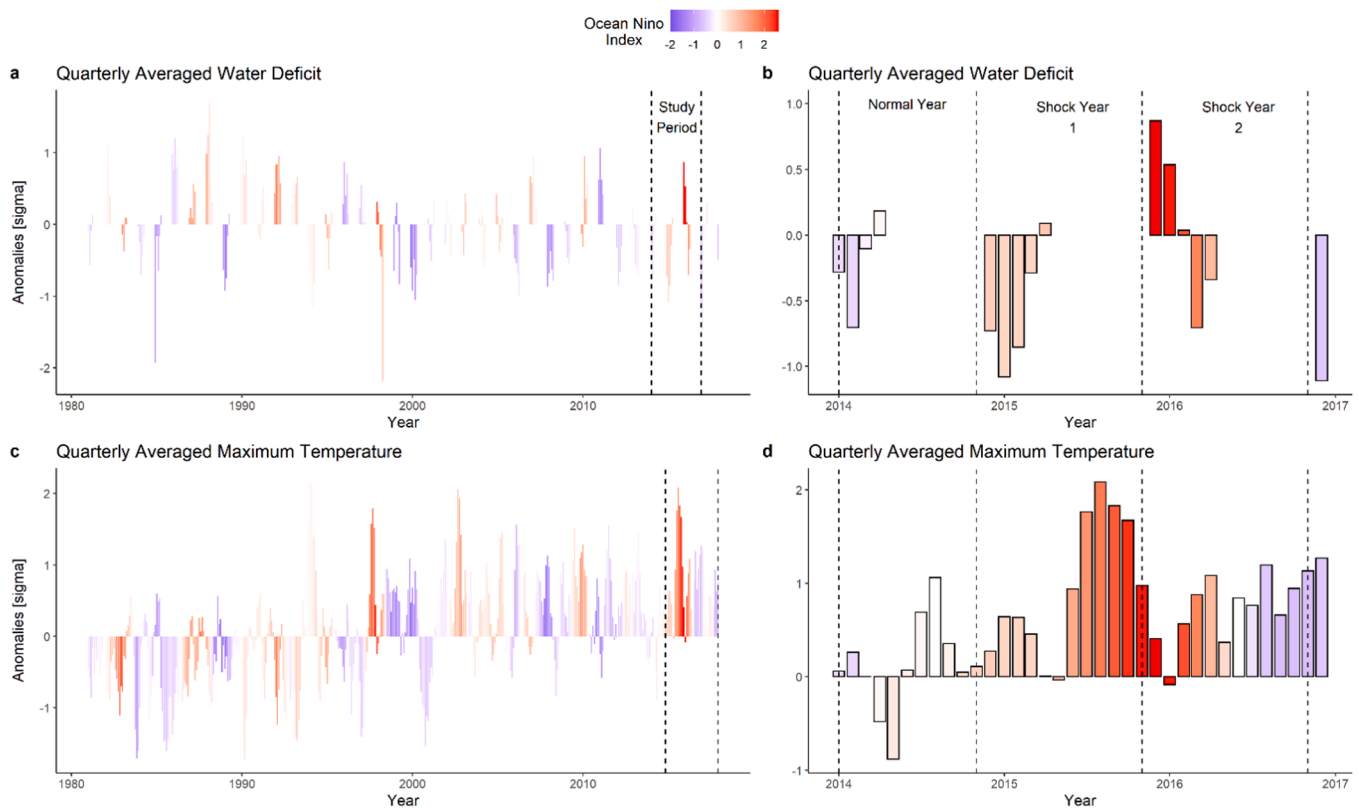


Fig. 1. Time series of anomalies of rolling 3-month averages of monthly water deficit (a) and monthly maximum temperature (b) derived from ERA5 data (Copernicus Climate Change Service (C3S), 2017). Anomalies calculated using 1980–2010 means as baseline conditions and normalised to be unitless. Shading delineates Ocean Niño Index (ONI) values. Dashed lines identify years covered by study period (2014–2016). (b & d) Zoom into anomaly estimates for the months relevant for coffee shrub flowering (January–February) to berry development (April–September) and harvesting (October–November) for each year of study.

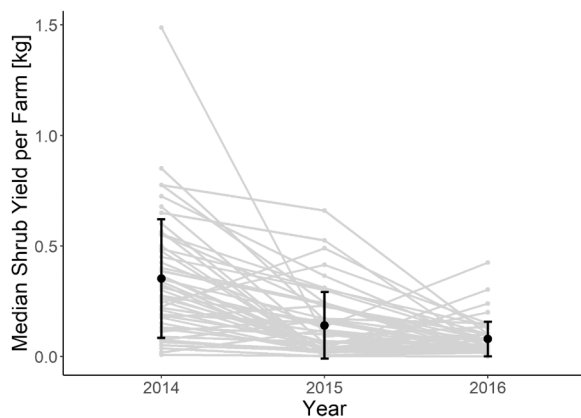


Fig. 2. Median-shrub measures per farm over three years of study period depicted in grey. Annual mean yields for all farms presented with standard errors in black, indicating clear reduction in landscape-level yields over study period.

(positive, $p < 0.05$) and a nonlinear relationship with canopy gap (positive, $p < 0.1$).

2.3. Variability in landscape and shade management influences over study period

Regarding variability in parameters impacting yield, both landscape and management parameters showed conflicting patterns over the study period. Plotting these landscape and shade management parameters for each yield model showed the complexity of these dynamics (Fig. 4).

From the top row, it is evident that elevation is consistently positive for yield, except when considering size of forest patch during a shock year. In this case, large patches at high elevation are especially negative for shrub yields (4c). On the other hand, the influences of shade management, suggest that more diverse shade correlates with lower shrub yields. This was more pronounced when considered with the presence of leguminous shade trees, showing a strong trade-off on yields between the two during a normal year (4e) and a less pronounced effect when modelling all three years together (4d). The negative influence of shade diversity was consistent when looking at influence of canopy openness, although canopy openness was of greater influence for the yield model of all three years (4f). During the normal year both shade diversity and canopy openness had negative influences on shrub yield (4g). Finally, while leguminous shade was broadly positive for shrub yields, the yield model for shock years suggested its interaction with canopy openness was especially influential on yields, with strongly positive impacts at high canopy openness (4h).

3. Discussion

3.1. Traditional influences on *C. arabica* yield

Berry and leaf fungal diseases are often-cited as among the primary influences of coffee shrub yield, and their incidence has been found to differ between intensively managed and shaded-systems (Zewdie et al., 2020). In this study, CBB (e.g. *Hypothenemus hampei*) was one of the significant negative influences on yield across all years and particularly during observed shock years. Globally CBB is expected to become a more prominent pest at higher elevations (Magrath and Ghazoul, 2015), particularly benefiting from rising temperatures in full-sun systems increasing the number of generations produced per fruiting season

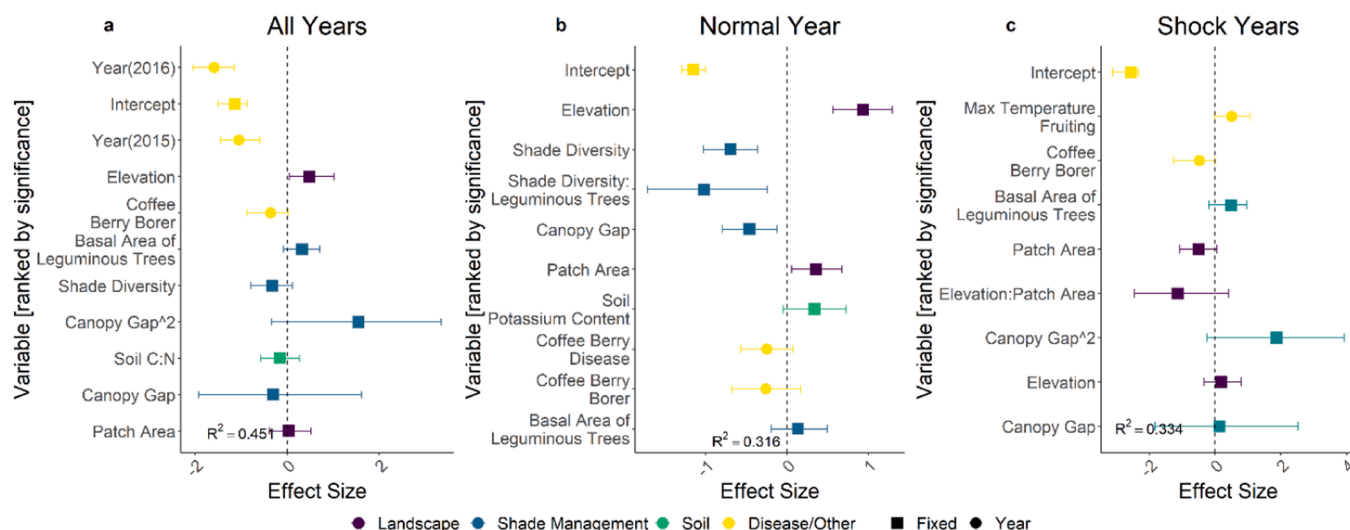


Fig. 3. Yield models for all years (a), normal year (b) and shock years (c), which include landscape, soil conditions, disease incidence and management influences that are either considered to be fixed (squares) or vary by year (circles). Error bars depict 90% confidence intervals. Tables S1, S2 and S3 detail significance and parameter values for each variable for the full and final models.

(Jaramillo et al., 2013, 2009). Previously, CBB was primarily found below 1500 m elevation; however, projections of future climate conditions in East Africa predict its presence will continue to reach higher elevations (Jaramillo et al., 2011). In this study, we confirmed presence of CBB above 1600 m.

Canopy openness is a prominent management parameter considered in agroforestry systems. We found both a linear negative influence (normal year) and positive non-linear influence (shock years) on coffee yields across our study period. Other studies have modelled the benefit of shade management at lower elevations to reduce yield losses dependent on competition for water between *C. arabica* and shade tree species (Rahn et al., 2018b). Unfortunately, our attempts to monitor continuous micro-climate were unsuccessful; therefore, we cannot comment on the influence of canopy openness on micro-climate over our gradients of interest. Our conflicting results across the climate shock may indicate there is not an optimal canopy openness consistent across elevation and patch area gradients in this landscape. The strength of canopy openness as an influence, however, compared to shade diversity and leguminous shade tree, does suggest that micro-climate impacts are stronger than potential nutrient or pest control impacts for coffee shrub yields.

Inter-annual variability of yields in *C. arabica* is regularly observed, requiring more long-term monitoring to understand its drivers. However, changes in rainfall are often the hypothesized driver (Meylan et al., 2017) and may vary in influence depending on whether the rainfall anomaly occurs during flowering or fruit development (Wang et al., 2015). Anecdotally, flowering appeared to be impacted by the shifting in rainfall over our study period; however, we had not been able to monitor flowering incidence in our “normal” year due to delays in plot establishment. In terms of the timing of the observed water deficit and temperature anomalies, the eco-physiological response of *C. arabica* to drought stress, measured as leaf water potential, around Yayu shows a strong seasonal pattern with only the dry season showing clear signs of stress (Melke and Fetene, 2014). Stomatal conductance of *C. arabica* leaves, an important function for photosynthesis, is negatively correlated with increasing air temperatures showing a maximum at 25 C (Melke and Fetene, 2014; Obso, 2006). Our analysis of ERA5 anomalies, suggested the first shock year had particularly strong drought conditions during the dry season, whereas maximum temperature anomalies up to two standard deviations above quarterly means could have been more relevant for the second shock year.

The significant positive influence of anomalies in maximum temperature during fruiting on shock yields is hard to explain, unless it is

more a proxy for the year of yield observation, due to the significant difference between the temperatures experienced and shrubs yields observed in 2015 (high, high) and 2016 (moderate, low). The compounding influences of two shock years in a row on a perennial shrub may have also been a factor, with the high temperature anomalies more impactful on the flowering and/or berry development in the following year.

3.2. Complementary versus trade-off drivers of yield

Having the benefit of observing this perennial system during baseline conditions before and then during a dramatic climate shock, we were able to document changes in sign in landscape and management influences on yields. This was particularly evident for landscape drivers of yield, with elevation and patch area exhibiting shifts between positive and negative effects. Under “normal” conditions, coffee shrub yields benefited from being located at higher elevation and within larger forest patches. During the shock years, elevation remained broadly positively correlated with yields, except in areas of large patches, showing a clear trade-off. When looking at the model for all three years, patch area has a relatively neutral effect, suggesting the dynamics between normal and shock years may have largely cancelled each other out. We are unclear of the mechanism for this shift in suitability; however, this finding suggests that there is not an optimum farm location in the landscape that is applicable for both “normal” years and those experiencing anomalously hot and/or dry conditions.

Longer term trends do suggest that higher elevations will be more suitable for *C. arabica* cultivation (Bunn et al., 2015; Davis et al., 2012; Moat et al., 2017; Ovalle-Rivera et al., 2015; Rahn et al., 2018a), a feature which is assumed to be primarily temperature-driven. Our results suggest that water availability, in addition to increasing temperatures, will remain a challenge if historically anomalous dry conditions become more frequent and should be considered in projections of suitability.

We found that canopy gap was the more influential shade management category for all years and exhibited trade-off dynamics. Its influence was either negative during “normal” year conditions or non-linear, where medium canopy openness was particularly negative for yields, during shock years. Presumably, this would vary with elevation and patch area, which was not explored explicitly in this analysis due to the limited number of observations in the available dataset.

Maintaining diverse shade had a largely negative effect on coffee

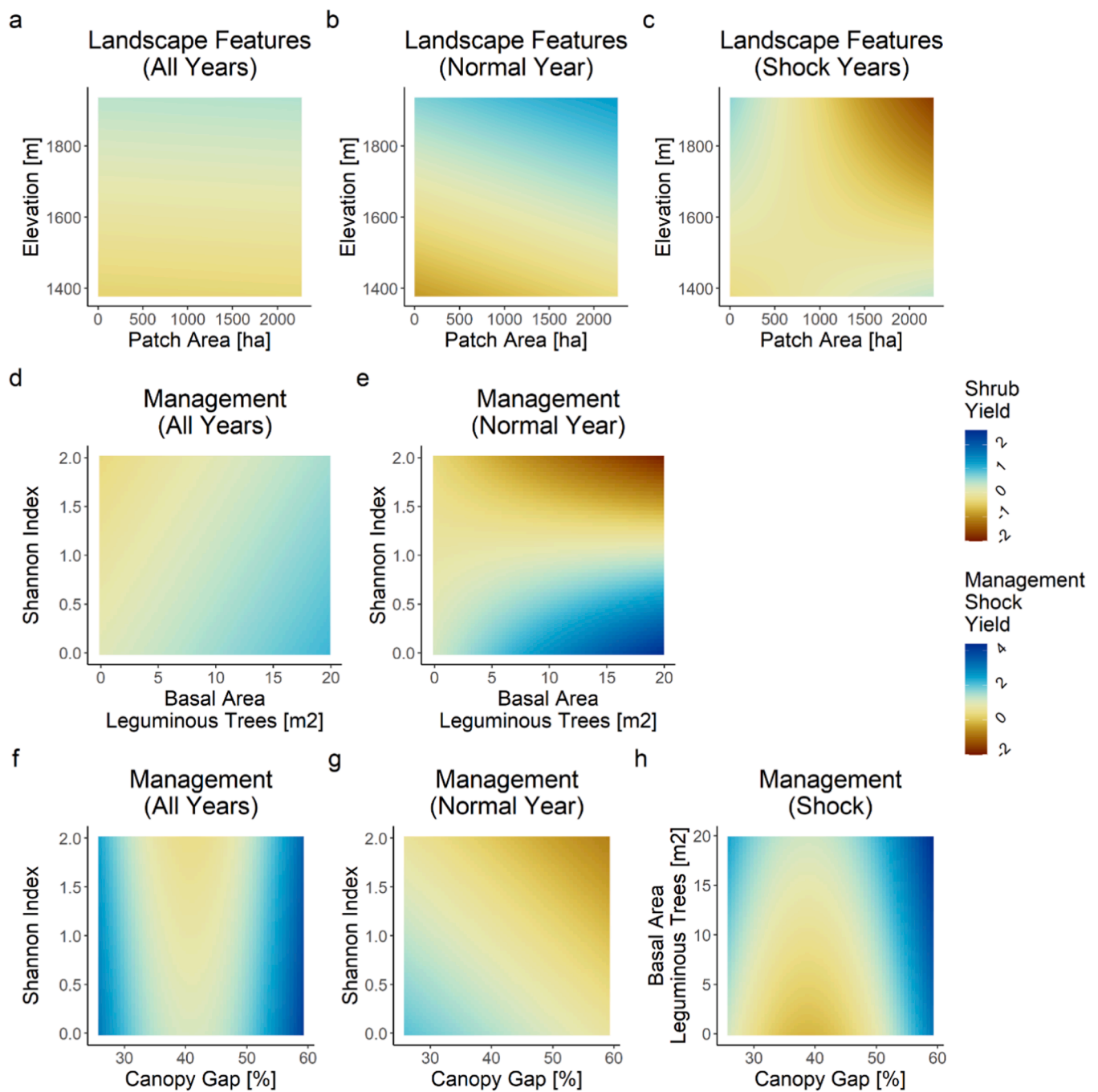


Fig. 4. Two-dimensional presentation of landscape (a-c) and shade management (d-h) influences on yields for all years (a, d, f), during the monitored “normal” year (b, e, g) and the two “shock” years (c, h), where parameters were present in the relevant yield model. Landscape features considered were elevation and area of patch a coffee farm was located within. Shade management features considered were basal area of leguminous shade trees, canopy gap and species diversity of shade trees, calculated using the Shannon index. A separate scale is presented for figure “h” due to a larger range of yield impact values.

yields during normal years, showing a particularly strong trade-off with increasing basal area of leguminous trees. This negative influence was less pronounced during the modelled shock years, suggesting either a limited influence on temperature and drought conditions experienced by coffee shrubs or a more mixed signal across farms. Other studies have found lower yield variability under more diverse shade, suggesting greater yield resistance to shocks under shaded systems (Cerda et al., 2017). This could be related to lower variability in micro-climate under shaded systems (Jaramillo et al., 2013) and/or reducing the intensity of flowering and by extension overbearing of berries (Vaast et al., 2016). Within the Ethiopian forest coffee system, intensity of management is

generally negatively related to shade tree diversity and positively related to dominance by early successional species (Hundera et al., 2012). We may be seeing evidence of this intensity of management in Fig. 4g, where low shade diversity and low canopy openness were beneficial for coffee yields in a normal year.

3.3. Implications for shade management

Intensive management of *C. arabica* was not common in this landscape; therefore, the options for improving yields we perceived were largely dependent on shade management. In general, choice of shade

trees needs to take into account their ability to bring water up from depth to shallower coffee roots, limited water demand during the dry season (e.g. deciduous) while also ameliorating temperature extremes (Vaast et al., 2016). Without addition of chemical fertilisers, nitrogen-fixing vegetation remains an important method for adding nutrients to this system, which we assume is driving the observed benefit to yields. *Albizia gummifera*, *Albizia grandibracteata* and *Acacia abyssinica* were the most common leguminous trees in our study system by basal area, often chosen due to their fast growth and wide-reaching crowns (Aerts et al., 2011). Assimilation of nitrogen from these species by coffee shrubs has already been observed (Meylan et al., 2017).

Agroforestry systems in particular can benefit from advances in understanding how intact and disturbed forests are likely to respond to increasingly frequent climate extremes and the importance of competitive advantages for tree species able to maximise their water-use (WUE) and nutrient-use efficiency (NUE) in regions expected to get drier and hotter (Shovon et al., 2020; Zhang et al., 2018). Leguminous trees are significantly more efficient for both WUE and NUE (Adams et al., 2016), and hence have been outcompeting both slower growing species and water demanding pioneer species in other parts of the world (Gei et al., 2018). Therefore, it would be important to explore whether the observed trade-off for yields between leguminous shade trees and diverse shade trees could relate to this dynamic and by extension be impacting water availability for understory coffee shrubs.

The complementarities and trade-offs between coffee yields and tree diversity are already a research subject of great interest, particularly the potential for coffee agroforestry systems to conserve biodiversity at the landscape scale (Tscharntke et al., 2012, 2011, 2005; Wanger et al., 2020). Our results do not contradict this potential, although we did not directly observe benefits of diverse shade for extreme climate shocks. However, a potential focus on planting an early successional species like the leguminous *A. gummifera*, also consistent with our findings, at the expense of late-successional species, may inhibit the regeneration potential of these forest coffee landscapes and reduce landscape-level resilience of this agroforestry system (Hundera et al., 2012). In this scenario, “regeneration potential” refers to the variety of tree species present and able to self-seed across the landscape. Should farmers show a preference for leguminous trees at the expense of a diverse shade cover, the potential for Afromontane tree species to migrate to higher elevations with climate change will be impeded. With climate suitability of *C. arabica* expected to move to higher elevations, managed migration may be necessary, including reforestation of previously deforested lands to achieve adequate shade cover. In this case, we would urge reforestation efforts to incorporate both leguminous and a diversity of local shade tree species.

3.4. Heterogeneous landscapes as a climate adaptation strategy

The trade-off between conserving biodiversity and maximising agricultural output in a landscape has often devolved to a debate around whether “land-sparing”, intensive agriculture in conjunction with strict conservation, or “land-sharing”, less productive agriculture more amenable for a variety of species to coexist, landscape configurations are preferable. However, it is rarely the reality where a landscape offers either homogeneous agricultural productivity potential or ideal habitat for biodiversity. Instead, a more heterogeneous configuration would be better for optimising both agricultural output and biodiversity conservation outcomes (Butsic et al., 2020; Vaast et al., 2016). The results of our study suggest there is neither an optimal location in the landscape nor an optimal landscape configuration to ensure coffee yield resilience to future climate extremes. Conservation of Ethiopian forest coffee landscapes is of global value, as many desired traits (e.g. disease resistance) are found in the wild *C. arabica* varieties currently residing in remaining forest areas and fragments, which have the ability to adapt to changing climate conditions (Aerts et al., 2017). Therefore, we would endorse the adoption of maintaining heterogeneous landscapes as a

viable climate adaptation strategy for the smallholder agroforestry sector.

3.5. Study limitations

While the yield model derived from our “normal” year observations revealed a number of significant predictors of shrub yield, the story was more mixed for the “all year” and “shock year” yield models. We developed our sampling strategy to be able to assess management and landscape influences on yield; however, we did not have the statistical power to fully capture the range of shrub responses along these axes during the two observed years of the climate shock. For the yield models including shock year observations, the year of monitoring or proxies for the year of monitoring (e.g. maximum temperature anomaly) were the strongest predictors of shrub yields. This could be due to the parameters we considered not being adequate to capture the range of adaptive responses or sources of stress to these shrubs, the limited ability of management or location in a landscape to offset the magnitude of the shock as well as the variability in coffee shrub responses due to greater genetic diversity across monitored farms that we were unable to capture in our analysis. We believe longer-term monitoring of these farming systems is needed along landscape and management gradients to capture more baseline data for comparison with shrub responses to sub-annual and multi-annual climate shocks.

4. Conclusion

Our study has revealed the value of continuous monitoring of a perennial crop over management and landscape gradients, which increases the likelihood of capturing inter-annual yield variability driven by climate changes. By taking a holistic approach to compare the strength of influence on yields by landscape and management factors, we observed surprising variability and trade-offs in yield impacts between normal and anomalous climate conditions. We feel these are important findings for development of climate smart agricultural practices, particularly for smallholder farmers with limited capacity to adapt to changing climate conditions. However, improving agroecological monitoring alone will not be enough to mitigate the vulnerability of low-input smallholder farmers to climate shocks acting over landscapes, especially if poor food security remains an impediment to adoption of adaptive measures. The response will need to be manifold and should include coordinating governance at multiple scales (Gbegbelegbe et al., 2018) and supporting improved social resilience more generally (Altieri and Nicholls, 2017). An important aspect of social resilience will be providing smallholder farmers near- to medium-term climate data and adequate capital to implement management recommendations (Cohn et al., 2017; Shikuku et al., 2017). There is an urgent imperative to support climate adaptation of smallholder farmers. Unfortunately, for our study system, we were unable to continue our household survey data collection through the state of emergency declared by the Ethiopian government and, therefore, cannot comment on the adaptive measures our study farmers have already been undertaking. Nevertheless, our results suggest a worrying trajectory for smallholder coffee agroforestry in Southwestern Ethiopia.

5. Materials and methods

5.1. Study site

The Yayu Coffee Forest Biosphere Reserve is located in the Ilubabur administrative zone of the Oromia Regional State in Ethiopia. It was registered in UNESCO’s World Network of Biosphere Reserves in 2010. It is a genetic pool for the protection of wild varieties of *Coffea arabica* and is divided into a core, buffer zone and transition area. Managing and harvesting coffee is permitted in the buffer and transition areas, the latter of which exhibits a heterogeneous landscape of variously sized

forest patches. Our study focused on two weredas, Yayu and Doraani, corresponding with lower elevation and higher elevation communities respectively.

5.2. Sampling gradients

This study monitored smallholder coffee farms over landscape and farm management gradients, located around the Yayu Coffee Forest Biosphere Reserve in Ethiopia (see Fig. 5) for three years (2014–2016). To establish landscape gradients of forest patchiness and elevation, nine contingencies were developed based on 3 levels of patch size and 3 categories of shade, which were then replicated over 2 elevation classes. Three replicates for each contingency and elevation class were established, for a total of 54 plots.

Forest areas were mapped using a cloud-free Landsat (USGS, 2014) image composite of the study region, derived from a 0.7 threshold of a Normalized Difference Vegetation Index (NDVI) layer. Patch size classes were based on calculated terciles of the natural log of identified forest areas. Elevation classes were identified as either above or below 1600 m using a Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (USGS, 2006). To establish a shade sampling gradient, we generated an accessibility mask based on distance from an all season road using, visited randomly generated points produced by The Sampling Design Tool in ArcGis 10 (ESRI, 2012) and averaged five canopy scope measurements (Hale and Brown, 2005) taken at the corners and centre of a 20 m by 20 plot per potential site. These canopy scope measures were then stratified into 3 classes of average shade intensity (low, medium and high). We then invited farmers to be a part of our study and established monitoring plots in February and March of 2014.

5.3. Plot design and data collection

On each farm a 20 m by 20 m-plot was established. In each plot, seven coffee shrubs were tagged (3 in the centre and one at each corner) and three branches (at 20 cm, 40 cm and 60 cm from the apex) from one

productive shoot of each shrub were regularly monitored from flowering to harvest over the three years. If tags were removed or branches had died, monitoring was shifted to a different productive stem or shrub in close proximity. Therefore, to minimise noise from shifting shrub and branch measurements throughout and between years, median shrub values were calculated per plot and harvesting year. Shrub monitoring data collected included number of open flowers and flower buds, number of berries, disease incidence on berries (e.g. coffee berry disease, CBD and coffee berry borer, CBB), disease incidence on leaves (coffee leaf rust, CLR), number of leaves and final harvest of all berries for each branch and the whole productive stem. Coffee density was estimated by measuring the number and DBH of all productive stems per shrub within a 10 m by 10 m area within the sampled plot.

Farm characteristics within plots were measured, including: percent canopy cover derived from the average of nine hemispherical canopy photos taken above the coffee canopy (3 m) as well as species, diameter at breast height (DBH) and height of shade trees. Soil samples were collected from all plots for the top 30 cm to assess bulk density, soil pH, soil texture, nutrient content (N, P, K, etc.), cation exchange capacity (CEC) and carbon content following ClimAfrica protocols (<https://www.climafrika.eu/>). Information about farm size and management variables (e.g. fertiliser or compost application, weeding, etc) were collated from a survey completed in February 2015 (details in Hiron et al., 2018). Following a state of emergency declared in the country, additional socio-economic surveys were not possible during the remaining shock years.

5.4. Climate data

We attempted to collect continuous micro-climate data across all of our plots, using a combination of Campbell Scientific under canopy ground stations (n=8) and Lascar EasyLog Temperature and Humidity USB Dataloggers (n=46). Unfortunately, the data collected from the USB dataloggers was often interrupted due to logger failure and missing equipment. For months where we had available data across our

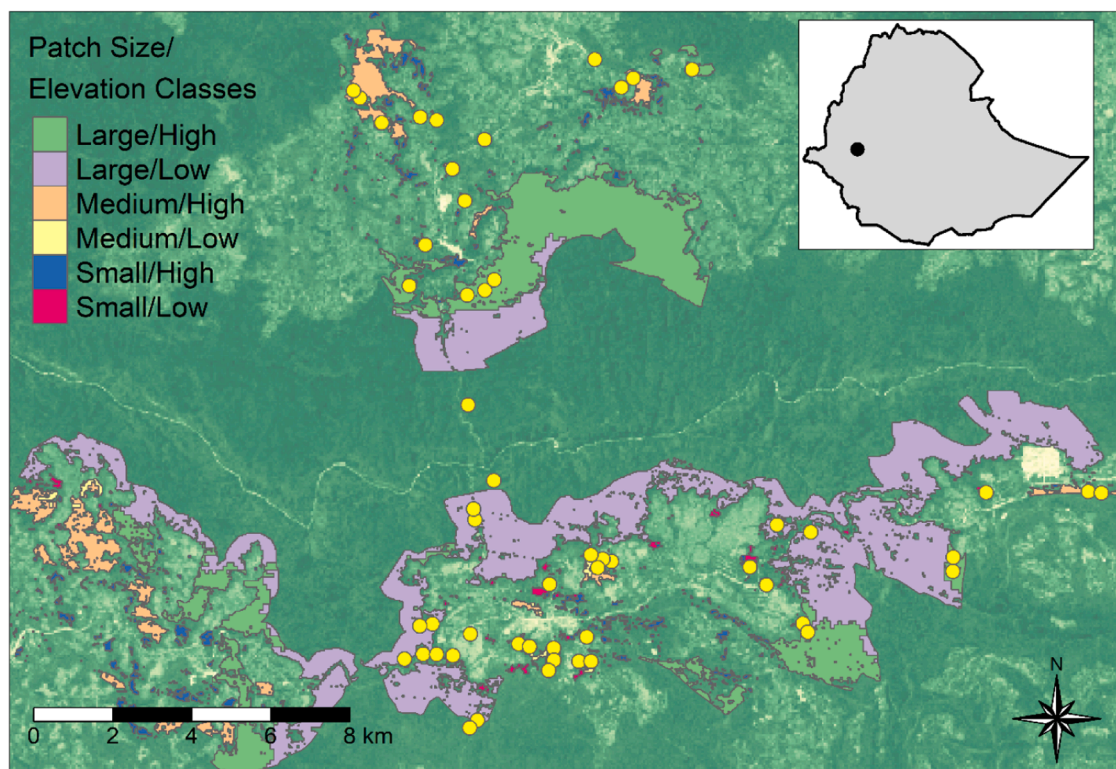


Fig. 5. Plot locations (yellow dots) across patch area and elevation classes. Inset shows approximate location of study area in Ethiopia.

landscape and management gradients, evaporative water demand was calculated per plot based on precipitation and radiation measurements made from two Campbell Scientific automatic weather stations established at two elevations (1960 m and 1620 m), to correspond with our altitudinal sampling strategy, and plot-level mean temperature using the equation from Turc (1961) (see Supplemental Materials for more details).

To estimate the climatic impact of the El Niño in our site, we used ERA5 data (Copernicus Climate Change Service (C3S), 2017), extracted from Google Earth Engine (Gorelick et al., 2017), for the time period 1980–2017. To assess the accuracy of ERA5 for our site, we regressed monthly measures with data from the Campbell Scientific climate station we established at 1960 m elevation (precipitation) and under the forest coffee canopy at 1750 m elevation (maximum temperature) (Figure S1). The resolution of ERA5 is ~28 km, therefore, more fine-scale comparisons were not possible. Without adequate meteorological data across Ethiopia for the reference time period, water deficit was calculated using the basic assumption that average monthly potential evapotranspiration is 55 mm based on estimates derived from contemporary measures (see Figure S2) and subtracting this value from monthly ERA5 precipitation estimates.

From these time series, we calculated monthly anomalies for maximum temperature and water deficit using the base dates of 1980–2010. We plotted normalised quarterly averages of monthly anomalies for maximum temperature and water deficit over our study period to assess the relative novelty of the shock, including the full time period to compare severity of conditions to previous El Niño events (Fig. 1). This was to assess the consistency of climatic conditions during El Niño events at this site, which are known to vary for regions of Africa (Malhi and Wright, 2004).

5.5. Data analysis

Climatic conditions during 2014 were considered to be relatively “normal” and were treated as a baseline for comparison with the El Niño conditions experienced during harvest years 2015 and 2016. The variables collected were intended to cover a range of ecosystem services hypothesized to impact coffee shrub productivity (see Figure S3). By taking a holistic approach, derived yield models for the normal and shock years attempted to capture the dominant influences on coffee shrub yields rather than considering each influence in isolation. To our knowledge, this is a novel approach to understanding landscape and management influences on coffee yields in combination.

For modelling the factors influencing shrub yields and resistance, we used the median harvest of all monitored shrubs per year as our dependent variable. Guided by our hypotheses of interacting influences we tested the significance of canopy gap (%), soil organic matter (% carbon), soil nitrogen limitation (C:N ratio), concentration of soil potassium (milliequivalents per 100 g), the mean DBH of measured coffee shrubs (cm, a proxy for farm age), whether a farm was located in the biosphere buffer (binary, proxy of limitations to shade management), proportion of berries with CBD (0–1), proportion of leaves with CLR (0–1), proportion of berries with evidence of CBB (0–1), total coffee area owned by the farmer (hectares, proxy for farmer wealth), the interaction between elevation (metres) and patch area (hectares) and the interaction between diversity of shade trees (Shannon Index) and basal area of leguminous trees (m^2/ha).

Models were developed for all years, the “normal” year and “shock” years separately, although they were all derived from the same full complement of parameters (see Tables S1, S2 and S3 for more detail). Non-significant factors and factors with high variable inflation were iteratively removed until the strongest predictors remained. Ninety percent boot-strap confidence intervals were calculated and are depicted in Fig. 3 and reported in Tables S1, S2 and S3. We plotted the distribution of model residuals and quantile-quantile probabilities to inform our choice of appropriate link function (see Figure S4). To be able to

compare parameter values between models, we used a gamma log-link, generalised linear model (GLM) for all models, with plot as a random effect and year as factor for our “all year” model and plot as a random effect for our “shock year” model. *lme4* (Bates et al., 2015) and *arm* (Gelman and Su, 2020) packages were used for analysis, *MuMIn* (Bartoń, 2023) was used for calculating GLM R-squared values and *tidyverse/ggplot2* (Wickham et al., 2019), *car* (Fox and Weisberg, 2019), *lattice* (Sarkar, 2008), *ggpubr* (Kassambara, 2020) and *patchwork* (Lin Pedersen, 2022) packages were used for figure generation.

The influence of landscape factors (e.g. elevation and patch area) and shade management factors (e.g. shade diversity, canopy gap and basal area of leguminous shade trees) were plotted for each year separately to visualise the influence of interactions on coffee shrub yields to reveal complementary and trade-off dynamics before and during the climate shock (Fig. 4).

CRedit authorship contribution statement

Mehrabi Zia: Writing – review & editing, Methodology, Data curation, Conceptualization. **Gonfa Techane:** Project administration, Methodology, Data curation. **Demissie Sheleme:** Methodology, Data curation. **Norris Ken:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Morel Alexandra C.:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Malhi Yadvinder:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Robinson Elizabeth J.Z.:** Writing – review & editing, Methodology, Funding acquisition, Formal analysis. **Boyd Emily:** Project administration, Funding acquisition. **McDermott Constance L.:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Mason John:** Writing – review & editing, Project administration, Funding acquisition. **Woldemariam Gole Tadesse:** Writing – review & editing, Resources, Project administration. **Hirons Mark A.:** Writing – review & editing, Project administration, Methodology, Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.agee.2024.108930](https://doi.org/10.1016/j.agee.2024.108930).

References

- Abdulai, I., Vaast, P., Hoffmann, M.P., Asare, R., Jassogne, L., Van Asten, P., Rötter, R.P., Graefe, S., 2018. Cocoa agroforestry is less resilient to sub-optimal and extreme climate than cocoa in full sun. *Glob. Change Biol.* 24, 273–286. <https://doi.org/10.1111/gcb.13885>.
- Adams, M.A., Turnbull, T.L., Sprent, J.I., Buchmann, N., 2016. Legumes are different: Leaf nitrogen, photosynthesis, and water use efficiency. *Proc. Natl. Acad. Sci. USA* 113, 4098–4103. <https://doi.org/10.1073/pnas.1523936113>.
- Aerts, R., Hundera, K., Berecha, G., Gijbels, P., Baeten, M., Van Mechelen, M., Hermy, M., Muys, B., Honnay, O., 2011. Semi-forest coffee cultivation and the conservation of Ethiopian Afromontane rainforest fragments. *For. Ecol. Manag.* 261, 1034–1041.
- Aerts, R., Geeraert, L., Berecha, G., Hundera, K., Muys, B., De Kort, H., Honnay, O., 2017. Conserving wild Arabica coffee: Emerging threats and opportunities. *Agric., Ecosyst. Environ.* 237, 75–79. <https://doi.org/10.1016/j.agee.2016.12.023>.
- Altieri, M.A., Nicholls, C.I., 2017. The adaptation and mitigation potential of traditional agriculture in a changing climate. *Clim. Change* 1–13.
- Bartoń, K., 2023. MuMIn: Multi-Model Inference.
- Bates, D., Mächler, M., Bolker, B., Wal, S., 2015. Fitting linear mixed-effects models using {lme4}. *J. Stat. Softw.* 67 (1), 48. <https://doi.org/10.18637/jss.v067.i01>.
- Beer, J., Muschler, R., Kass, D., Somarriva, E., 1998. Shade management in coffee and cacao plantations. *Agrofor. Syst.* 38, 139–164.
- Blaser, W.J., Oppong, J., Hart, S.P., Landolt, J., Yeboah, E., Six, J., 2018. Climate-smart sustainable agriculture in low-to-intermediate shade agroforests. *Nat. Sustain.* 1, 234–239. <https://doi.org/10.1038/s41893-018-0062-8>.
- Bunn, C., Läderach, P., Ovalle Rivera, O., Kirschke, D., 2015. A bitter cup: climate change profile of global production of Arabica and Robusta coffee. *Clim. Change* 129, 89–101. <https://doi.org/10.1007/s10584-014-1306-x>.
- Butsic, V., Kuemmerle, T., Pallud, L., Helmstedt, K.J., Macchi, L., Potts, M.D., 2020. Aligning biodiversity conservation and agricultural production in heterogeneous landscapes. *Ecol. Appl.* 30, e02057 <https://doi.org/10.1002/eap.2057>.
- Copernicus Climate Change Service (C3S), 2017. ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service Climate Data Store (CDS), (accessed July 2019).
- Camargo, M.B.P. de, 2010. The impact of climatic variability and climate change on arabic coffee crop in Brazil. *Bragantia* 69, 239–247. <https://doi.org/10.1590/S0006-87052010000100030>.
- Cerda, R., Allinne, C., Gary, C., Tixier, P., Harvey, C.A., Krolczyk, L., Mathiot, C., Clément, E., Aubertot, J.-N., Avelino, J., 2017. Effects of shade, altitude and management on multiple ecosystem services in coffee agroecosystems. *Eur. J. Agron.* 82, 308–319. <https://doi.org/10.1016/j.eja.2016.09.019>.
- Cohn, A.S., Newton, P., Gil, J.D.B., Kuhl, L., Samberg, L., Ricciardi, V., Manly, J.R., Northrop, S., 2017. Smallholder Agriculture and Climate Change. *Annu. Rev. Environ. Resour.* 42, 347–375. <https://doi.org/10.1146/annurev-environ-102016-060946>.
- Davis, A.P., Gole, T.W., Baena, S., Moat, J., 2012. The impact of climate change on indigenous arabica coffee (*Coffea arabica*): predicting future trends and identifying priorities. *PLoS ONE* 7, e47981. <https://doi.org/10.1371/journal.pone.0047981.t001>.
- ESRI, 2012. ArcGIS Desktop: Release 10.1. California.
- Fox, J., Weisberg, S., 2019. An {R} Companion to Applied Regression, Third. ed. Sage, Thousand Oaks, CA.
- Garedew, W., Lemessa, F., Hailu, B.T., Pinard, F., 2020. Influence of plot features and landscape structure on the epidemics of coffee berry disease (*Colletotrichum kahawae* Waller & Bridge) in southwest Ethiopia. *Int. J. Pest Manag.* 1–9. <https://doi.org/10.1080/09670874.2020.1752956>.
- Gbegebege, S., Serem, J., Stirling, C., Kyazze, F., Radeny, M., Misiko, M., Tongruksawattana, S., Nafula, L., Gakii, M., Sonder, K., 2018. Smallholder farmers in eastern Africa and climate change: a review of risks and adaptation options with implications for future adaptation programmes. *Clim. Dev.* 10, 289–306.
- Geeraert, L., Aerts, R., Jordaens, K., Dox, I., Wellens, S., Couri, M., Berecha, G., Honnay, O., 2019. Intensification of Ethiopian coffee agroforestry drives impoverishment of the Arabica coffee flower visiting bee and fly communities. *Agrofor. Syst.* 93, 1729–1739. <https://doi.org/10.1007/s10457-018-0280-0>.
- Gei, M., Rozendaal, D.M.A., Poorter, L., Bongers, F., Sprent, J.I., Garner, M.D., Aide, T. M., Andrade, J.L., Balvanera, P., Becknell, J.M., Brancalion, P.H.S., Cabral, G.A.L., César, R.G., Chazdon, R.L., Cole, R.J., Colletta, G.D., de Jong, B., Denslow, J.S., Dent, D.H., DeWalt, S.J., Dupuy, J.M., Durán, S.M., do Espírito Santo, M.M., Fernandes, G.W., Nunes, Y.R.F., Finegan, B., Moser, V.G., Hall, J.S., Hernández-Stefanoni, J.L., Junqueira, A.B., Kennard, D., Lebrija-Trejos, E., Letcher, S.G., Lohbeck, M., Marin-Spiotta, E., Martínez-Ramos, M., Meave, J.A., Menge, D.N.L., Mora, F., Muñoz, R., Muscarella, R., Ochoa-Gaona, S., Orihuela-Belmonte, E., Ostertag, R., Peña-Claros, M., Pérez-García, E.A., Piotta, D., Reich, P.B., Reyes-García, C., Rodríguez-Velázquez, J., Romero-Pérez, I.E., Sanaphre-Villanueva, L., Sanchez-Azofeifa, A., Schwartz, N.B., de Almeida, A.S., Almeida-Cortez, J.S., Silver, W., de Souza Moreno, V., Sullivan, B.W., Swenson, N.G., Uriarte, M., van Breugel, M., van der Wal, H., Veloso, M. das D.M., Vester, H.F.M., Vieira, I.C.G., Zimmerman, J.K., Powers, J.S., 2018. Legume abundance along successional and rainfall gradients in Neotropical forests. *Nat. Ecol. Evol.* 2, 1104–1111. <https://doi.org/10.1038/s41559-018-0559-6>.
- Gelman, A., Su, Y.-S., 2020. arm: Data Analysis Using Regression and Multilevel/Hierarchical Models.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google earth engine: planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* <https://doi.org/10.1016/j.rse.2017.06.031>.
- Grass, I., Jauker, B., Steffan-Dewenter, I., Tschamtké, T., Jauker, F., 2018. Past and potential future effects of habitat fragmentation on structure and stability of plant-pollinator and host-parasitoid networks. *Nat. Publ. Group* 1–13.
- Gunathilaka, R.P.D., Smart, J.C.R., Fleming, C.M., 2018. Adaptation to climate change in perennial cropping systems: options, barriers and policy implications. *Environ. Sci. Policy* 82, 108–116. <https://doi.org/10.1016/j.envsci.2018.01.011>.
- Hale, S.E., Brown, N., 2005. Use of the canopy-scope for assessing canopy openness in plantation forests. *Forestry* 78, 365–371. <https://doi.org/10.1093/forestry/cpi043>.
- Hirons, M., Robinson, E., McDermott, C., Morel, A., Asare, R., Boyd, E., Gonfa, T., Gole, T.W., Malhi, Y., Mason, J., Norris, K., 2018. Understanding poverty in cash-crop agro-forestry systems: evidence from Ghana and Ethiopia. *Ecol. Econ.* 154, 31–41. <https://doi.org/10.1016/j.ecolecon.2018.07.021>.
- Huang, B., Thorne, P.W., Banzon, V.F., Boyer, T., Chepurin, G., Lawrimore, J.H., Menne, M.J., Smith, T.M., Vose, R.S., Zhang, H.-M., 2017. Extended reconstructed sea surface temperature, version 5 (ERSSTv5): upgrades, validations, and intercomparisons. *J. Clim.* 30, 8179–8205. <https://doi.org/10.1175/JCLI-D-16-0836.1>.
- Hundera, K., Aerts, R., Fontaine, A., Van Mechelen, M., Gijbels, P., Honnay, O., Muys, B., 2012. Effects of coffee management intensity on composition, structure, and regeneration status of Ethiopian moist evergreen afro-montane forests. *Environ. Manag.* 51, 801–809.
- Jaramillo, J., Chabi-Olaye, A., Kamonjo, C., Jaramillo, A., Vega, F.E., Poehling, H.-M., Borgemeister, C., 2009. Thermal tolerance of the coffee berry borer hypotenemus Hampei: predictions of climate change impact on a tropical insect pest. *PLoS ONE* 4, e6487. <https://doi.org/10.1371/journal.pone.0006487>.
- Jaramillo, J., Muchugu, E., Vega, F.E., Davis, A., Borgemeister, C., Chabi-Olaye, A., 2011. Some Like It Hot: The Influence and Implications of Climate Change on Coffee Berry Borer (*Hypothenemus hampei*) and Coffee Production in East Africa. *PLoS ONE* 6, e24528.
- Jaramillo, J., Setamou, M., Muchugu, E., Chabi-Olaye, A., Jaramillo, A., Mukabana, J., Maina, J., Gathara, S., Borgemeister, C., 2013. Climate Change or Urbanization? Impacts on a traditional coffee production system in East Africa over the last 80 years. *PLoS ONE* 8, e51815.
- Jha, S., Bacon, C.M., Philpott, S.M., Ernesto Mendez, V., Läderach, P., Rice, R.A., 2014. Shade coffee: update on a disappearing refuge for biodiversity. *BioScience* 64, 416–428.
- Jucker, T., Hardwick, S.R., Both, S., Elias, D.M.O., EWERS, R.M., Milodowski, D.T., Swinfield, T., Coomes, D.A., 2018. Canopy structure and topography jointly constrain the microclimate of human-modified tropical landscapes. *Glob. Change Biol.* 65, 105.
- Jury, M.R., Funk, C., 2012. Climatic trends over Ethiopia: regional signals and drivers. *Int. J. Climatol.* 33, 1924–1935.
- Kassambara, A., 2020. ggpubr: “ggplot2” Based Publication Ready Plots.
- Lin, B.B., Perfecto, I., Vandermeer, J., 2008. Synergies between agricultural intensification and climate change could create surprising vulnerabilities for crops. *BioScience* 58, 847–854. <https://doi.org/10.1641/B580911>.
- Lin Pedersen, T., 2022. patchwork: The Composer of Plots.
- Magrath, A., Ghazoul, J., 2015. Climate and pest-driven geographic shifts in global coffee production: implications for forest cover, biodiversity and carbon storage. *PLoS ONE* 1–15.
- Malhi, Y., Wright, J., 2004. Spatial patterns and recent trends in the climate of tropical rainforest regions. *Philos. Trans. R. Soc. Lond. Ser. B: Biol. Sci.* 359, 311–329. <https://doi.org/10.1098/rstb.2003.1433>.
- Melke, A., Fetene, M., 2014. Eco-physiological basis of drought stress in coffee (*Coffea arabica*, L.) in Ethiopia. *Theor. Exp. Plant Physiol.* 26, 225–239.
- Meylan, L., Gary, C., Allinne, C., Ortiz, J., Jackson, L., Rapidel, B., 2017. Evaluating the effect of shade trees on provision of ecosystem services in intensively managed coffee plantations. *Agric., Ecosyst. Environ.* 245, 32–42.
- Moat, J., Williams, J., Baena, S., Wilkinson, T., Gole, T.W., Challa, Z.K., Demissew, S., Davis, A.P., 2017. Resilience potential of the Ethiopian coffee sector under climate change. *Nat. Plants* 3, 17081. <https://doi.org/10.1038/nplants.2017.81>.
- Morel, A.C., Hirons, M., Demissie, S., Gonfa, T., Mehrabi, Z., Long, P.R., Rifai, S., Woldemariam Gole, T., Mason, J., McDermott, C.L., Boyd, E., Robinson, E.J.Z., Malhi, Y., Norris, K., 2019b. The structures underpinning vulnerability: examining landscape-society interactions in a smallholder coffee agroforestry system. *Environ. Res. Lett.* 14, 075006 <https://doi.org/10.1088/1748-9326/ab2280>.
- Morel, A.C., Hirons, M., Adu Sasu, M., Quaye, M., Ashley Asare, R., Mason, J., Adu-Bredu, S., Boyd, E., McDermott, C.L., Robinson, E.J.Z., Straser, R., Malhi, Y., Norris, K., 2019a. The Ecological limits of poverty alleviation in an African forest-agriculture landscape. *Front. Sustain. Food Syst.* 3, 57. <https://doi.org/10.3389/fsufs.2019.00057>.
- NOAA, 2019. Cold & Warm Episodes by Season (Oceanic Nino Index) [WWW Document]. Climate Prediction Center. URL (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php).
- Obso, T.K., 2006. Ecophysiological diversity of wild Arabica coffee populations in Ethiopia: Growth, water relations and hydraulic characteristics along a climatic gradient (Doctoral Dissertation). Cent. Dev. Res. ZEF, Bonn.
- Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., Schroth, G., 2015. Projected shifts in coffee arabica suitability among major global producing regions due to climate change. *PLoS ONE* 10, e0124155.
- Perfecto, I., Vandermeer, J., Philpott, S.M., 2014. Complex ecological interactions in the coffee agroecosystem. *Annu. Rev. Ecol. Syst.* 45, 137–158.
- Rahn, E., Liebig, T., Ghazoul, J., van Asten, P., Läderach, P., Vaast, P., Sarmiento, A., Garcia, C., Jassogne, L., 2018a. Opportunities for sustainable intensification of coffee agro-ecosystems along an altitudinal gradient on Mt. Elgon, Uganda. *Agric., Ecosyst. Environ.* 263, 31–40.

- Rahn, E., Vaast, P., Läderach, P., van Asten, P., Jassogne, L., Ghazoul, J., 2018b. Exploring adaptation strategies of coffee production to climate change using a process-based model. *Ecol. Model.* 371, 76–89. <https://doi.org/10.1016/j.ecolmodel.2018.01.009>.
- Ribot, J.C., Peluso, N.A., 2003. A theory of access. *Rural Sociol.* 68, 153–181.
- Rifai, S.W., Li, S., Malhi, Y., 2019. Coupling of El Niño events and long-term warming leads to pervasive climate extremes in the terrestrial tropics. *Environ. Res. Lett.* 14, 105002 <https://doi.org/10.1088/1748-9326/ab402f>.
- Sarkar, D., 2008. *Lattice: Multivariate Data Visualization with R*. Springer, New York.
- Schmidt, M., Nendel, C., Funk, R., Mitchell, M.G.E., Lischeid, G., 2019. Modeling yields response to shading in the field-to-forest transition zones in heterogeneous landscapes. *Agriculture* 9, 6. <https://doi.org/10.3390/agriculture9010006>.
- Shikuku, K.M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J.G., Mwangera, C., Läderach, P., 2017. Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Clim. Risk Manag.* 16, 234–245. <https://doi.org/10.1016/j.crm.2017.03.001>.
- Shovon, T.A., Rozendaal, D.M.A., Gagnon, D., Gendron, F., Vetter, M., Vanderwel, M.C., 2020. Plant communities on nitrogen-rich soil are less sensitive to soil moisture than plant communities on nitrogen-poor soil. *J. Ecol.* 108, 133–144. <https://doi.org/10.1111/1365-2745.13251>.
- Tscharntke, T., Klein, A.M., Kruess, A., Steffan-Dewenter, I., Thies, C., 2005. Landscape perspectives on agricultural intensification and biodiversity – ecosystem service management. *Ecol. Lett.* 8, 857–874. <https://doi.org/10.1111/j.1461-0248.2005.00782.x>.
- Tscharntke, T., Clough, Y., Bhagwat, S.A., Buchori, D., Faust, H., Hertel, D., Hölscher, D., Jührbandt, J., Kessler, M., Perfecto, I., Scherber, C., Schroth, G., Veldkamp, E., Wanger, T.C., 2011. Multifunctional shade-tree management in tropical agroforestry landscapes – a review. *J. Appl. Ecol.* 48, 619–629. <https://doi.org/10.1111/j.1365-2664.2010.01939.x>.
- Tscharntke, T., Clough, Y., Wanger, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., Whitbread, A., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. *Biol. Conserv.* 151, 53–59. <https://doi.org/10.1016/j.biocon.2012.01.068>.
- Turc, L., 1961. Estimation of irrigation water requirements, potential evapotranspiration: a simple climatic formula evolved up to date. *Ann. Agron.* 12, 13–49.
- USGS, 2006. Shuttle Radar Topography Mission. Global Land Cover Facility, Maryland.
- USGS, 2014. Landsat Level- 2 Surface Reflectance Science Product courtesy of the U.S. Geological Survey.
- Vaast, P., Harmand, J.-M., Rapidel, B., Jagoret, P., Deheuvels, O., 2016. Coffee and Cocoa Production in Agroforestry—A Climate-Smart Agriculture Model. In: Torquebiau, E. (Ed.), *Climate Change and Agriculture Worldwide*. Springer Netherlands, Dordrecht, pp. 209–224. https://doi.org/10.1007/978-94-017-7462-8_16.
- Wang, N., Jassogne, L., Van Asten, P.J.A., Mukasa, D., Wanyama, I., Kagezi, G., Giller, K. E., 2015. Evaluating coffee yield gaps and important biotic, abiotic, and management factors limiting coffee production in Uganda. *Eur. J. Agron.* 63, 1–11.
- Wanger, T.C., DeClerck, F., Garibaldi, L.A., Ghazoul, J., Kleijn, D., Klein, A.-M., Kremen, C., Mooney, H., Perfecto, I., Powell, L.L., Settele, J., Solé, M., Tscharntke, T., Weisser, W., 2020. Integrating agroecological production in a robust post-2020 Global Biodiversity Framework. *Nat. Ecol. Evol.* 4, 1150–1152. <https://doi.org/10.1038/s41559-020-1262-y>.
- Wickham, H., Averick, M., Bryan, J., Chang, W., D'Agostino McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Lin Pedersen, T., Miller, E., Milton Bache, S., Müller, K., Ooms, J., Robinson, D., Paige Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the {tidyverse}. *J. Open Source Softw.* 4, 1686. <https://doi.org/10.21105/joss.01686>.
- Zewdie, B., Tack, A.J.M., Adugna, G., Nemomissa, S., Hylander, K., 2020. Patterns and drivers of fungal disease communities on Arabica coffee along a management gradient. *Basic Appl. Ecol.* 47, 95–106. <https://doi.org/10.1016/j.baae.2020.05.002>.
- Zhang, T., Niinemets, Ü., Sheffield, J., Lichstein, J.W., 2018. Shifts in tree functional composition amplify the response of forest biomass to climate. *Nature* 1–18.