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# Agricultural diversification for crop yield stability: A smallholder adaptation strategy to climate variability in Ethiopia

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## Abstract

Climate variability threatens food system stability, particularly among smallholders in developing countries who depend on rainfed agriculture. Farm diversification could be a relevant adaptation strategy in this context as a greater number of species or a more even distribution of crops is postulated to have a stabilizing effect on farm output as compared to a homogeneous farm. In this study, we aimed to explore relationships between climate variability, agricultural diversity, and crop yield stability. We used agriculture-focused panel data from Ethiopian households surveyed over four waves from 2011 to 2018 and two climate datasets to derive measures of long- and short-term climate variability. In a twofold analytical approach, we used mixed effects models to separately model (i) farm richness and pastoralism prevalence with climate variability as predictors, and (ii) crop yield stability with diversity, farm input, and climate characteristics as predictors. We found that farm diversity is highest in areas with high temperature variability, or low rainfall variability. This held even when excluding pastoralists households, who have naturally lower diversity. We further showed that pastoralism is least common in areas with high temperature variability and low month-to-month rainfall variability. Both crop richness and crop evenness positively affected temporal yield stability, with each showing a greater effect than irrigation, fertilizer, and pesticide usage. Together, these findings suggest that shifts in typical ranges of climate variability could destabilize farm-level crop yield for smallholders by limiting diversification opportunities. Our findings highlight the need for researchers and policymakers to consider not only the direct effects of climate variability on crop yield, but also its indirect effects on yield stability caused by increasingly limited adaptation choices.

**Keywords:** Agricultural diversity; Yield stability; Climate variability; Ethiopia; Smallholder farmers

## 39 Introduction

40 Ensuring food stability under increased climate variability is a priority for food security and livelihoods,  
41 especially in lower-income and low-latitude tropical countries, which are likely to be hit hardest by  
42 the effects of climate change (Rosenzweig and Parry 1994; Rosenzweig et al. 2014; Callahan and  
43 Mankin 2022). In particular, there is medium to high confidence that climate change has already  
44 increased heat waves and droughts in sub-Saharan Africa, with detrimental impacts on agricultural  
45 productivity and efficiency (Otto et al. 2018; Chiang et al. 2021; Trisos et al. 2022). Increases in climate  
46 variability are responsible for both a large proportion of global yield variability in several prominent  
47 crops (Ray et al. 2015), and a reduction in national temporal yield stability as a result of destabilizing  
48 individual crop yields (Mahaut et al. 2021). Livestock is also at risk of increasing climate variability. For  
49 example, higher drought frequency can increase mortality and decrease productivity (Herrero et al.  
50 2010; Godde et al. 2019). Smallholders are especially vulnerable to increased climate variability due  
51 to their high dependence on agriculture for their livelihoods, their strong orientation towards rainfed  
52 agricultural systems, and their often-limited capacity to cope and adapt to shocks (Ochieng et al. 2020;  
53 FAO 2021). Among the global pastoral communities, those that are currently the most socio-  
54 economically vulnerable are expected to also experience the most damaging vegetation trends for  
55 livestock production (Sloat et al. 2018; Godde et al. 2020). Such findings highlight the need among  
56 smallholders to adopt adaptation strategies that minimize crop and livestock production risks, stabilize  
57 yields, and thus improve food security.

58

59 Diversification has been suggested as a risk management strategy to adapt to climate variability and  
60 shocks. It involves increasing the variety, balance, or disparity of crops or livestock activities, which  
61 broadens the farm system's range of ecological responses to adverse conditions (Stirling 2007; Lin  
62 2011). Both crop and livestock diversification can generally increase food security (Waha et al. 2022)  
63 although the degree to which it improves food security may be limited to a threshold (Das and Ganesh-  
64 Kumar 2018; Waha et al. 2018; Parvathi 2018). This indicates that finding the best levels for each type  
65 of diversity may be preferred over maximizing all aspects of diversity (Renard & Tilman, 2019). Benefits  
66 of diversification for food security include pest and disease suppression (Lin 2011), reduced income  
67 variability and greater market opportunities (Bellon et al. 2020; Mzyece and Ng'ombe 2021), reduced  
68 poverty (Michler and Josephson 2017), and lower downside risk exposure for crop income (Bozzola  
69 and Smale 2020). Such benefits may not always outweigh the resources required for smallholders to  
70 implement and maintain diversification strategies, such as the financial costs, extra labour, and  
71 knowledge (Rosa-Schleich et al. 2019). However, the ability to optimize diversification based on the  
72 farmer's specific needs makes it a promising candidate for adaptation to climate variability.

73

74 While initial evidence and theory suggests a general positive effect of diversification on food security,  
75 the specific effects of diversification on temporal yield stability are still poorly understood (Beillouin  
76 et al. 2019), especially at the household level and over multiple years to decadal time scales. Literature  
77 to date offers some informative theory and observations pertaining to the effect of diversity on  
78 stability over time. For example, crop diversification at the national level stabilizes food production  
79 among many countries (Renard and Tilman 2019), including several in sub-Saharan Africa. This may  
80 be explained by the results of Mahaut et al. (2021), who found that the average yield stability of  
81 individual crops and asynchronization of yield fluctuations are both important determinants for  
82 national food production stability, and that crop diversification may improve the latter. Cereal  
83 intercropping with legumes was also found to significantly reduce the high instability of cereal yields  
84 in tropical regions (Raseduzzaman and Jensen 2017). Exploring the diversity-stability relationship at  
85 the household level with panel data can provide valuable additional insights. Indeed, as drivers of  
86 stability can depend on spatial scale (Shanafelt et al. 2015; Egli et al. 2021), household level analyses  
87 are imperative to forming valid conclusions about smallholder adaptation strategies. Moreover, the  
88 conditions faced by a household may differ significantly based on the unique combination of issues  
89 from the local scale to the global scale (Urruty et al. 2016). This heterogeneity in household responses  
90 is not considered in national-level or regional-level studies.

91

92 Here, we aim to explore the relationships between climate variability, farm diversity, and temporal  
93 yield stability with a case study in Ethiopia, using household survey panel data from rural smallholders.  
94 We accomplish this through two interrelated aims. Firstly, we aim to better understand the nature of  
95 the relationship between observed climate variability and farm diversity. Secondly, we aim to  
96 investigate any association between farm diversity and temporal yield stability. In addressing these  
97 aims, we make the following hypotheses: diversity is non-linearly associated with climate variability,  
98 such that diversity is highest at a moderate range, and lowest at the extremes of climate variability;  
99 farm livestock orientation is positively associated with climate variability; and temporal yield stability  
100 is positively associated with diversity.

101

## 102 **Data**

### 103 **Household survey data**

104 The World Bank's Living Standard's Measurement Study Integrated Surveys on Agriculture is a  
105 collection of agriculture-focused household surveys which provide comprehensive panel data across

106 several countries in sub-Saharan Africa. We used the Ethiopia panel dataset, which contains four  
107 waves pertaining to the primary harvest season, also called the Meher season, in 2011, 2013, 2015,  
108 and 2018 (Central Statistics Agency of Ethiopia 2011, 2013, 2015, 2018).

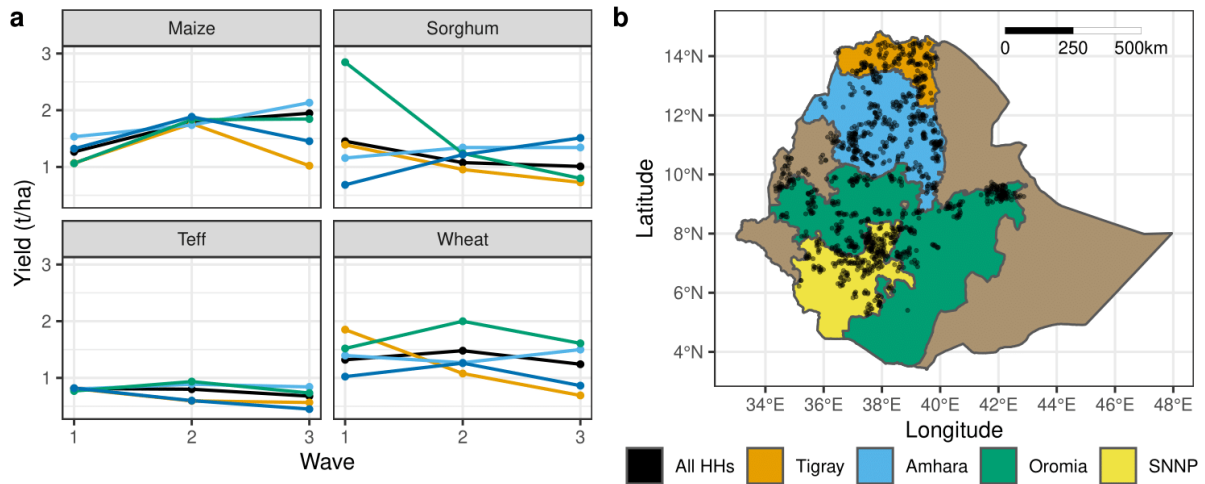
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110 The analysis was disaggregated into two distinct parts corresponding to the aims of this study, and  
111 each part uses different survey waves. Firstly, we analyzed the relationship between farm diversity  
112 and climate variability using cross-sectional household survey data from wave 4 in 2018. Secondly, we  
113 used household survey data from previous waves 1 to 3 to perform a longitudinal analysis investigating  
114 the effect of diversity on temporal yield stability. The latest survey wave from 2018 is a refreshed  
115 sample, and so it was not possible to link at the household level with the previous waves (CSA and  
116 World Bank 2021). Moreover, using wave 4 for the first objective rather than wave 1 to 3 ensured that  
117 the analysis was representative for all regions sampled. Indeed, the survey design for wave 1 to 3 was  
118 not intended to provide regional representativity across all regions.

119

120 We considered only rural households, and only those households that harvested crops in the most  
121 recent Meher season, or owned livestock in the past 12 months. Crop yields vary a lot from year to  
122 year and between different regions (Fig. 1a). Due to the survey design, the distribution of households  
123 within and across each region Ethiopia's largest administrative division is largely dependent on  
124 population density (Fig. 1b). For example, for wave 4, 1562 out of the 2521 rural households used in  
125 our analysis are from Tigray, Amhara, Oromia, or the Southern Nations, Nationalities, and Peoples'  
126 Region. The remaining households come from the other six, typically smaller, regions. Notable  
127 exceptions to this are Somali and Afar, both rather large pastoral/agro-pastoral regions, with 49 and  
128 268 households respectively. The first three waves have a different distribution, due to the refreshed  
129 sampling for wave 4 (CSA and World Bank 2021). The World Bank's GPS anonymization process sees  
130 each household take the coordinates of its kebele – Ethiopia's smallest administrative division - which  
131 is then randomly offset by 0-5km, with 1% of kebeles being offset by an additional 0-10km. Each  
132 kebele's GPS coordinate is guaranteed to be within its correct zone - Ethiopia's second-largest  
133 administrative division (CSA and World Bank 2021).

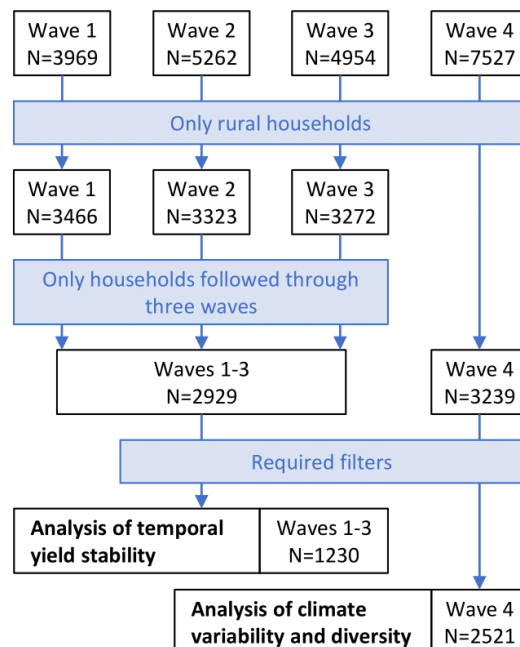
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Fig. 1: Temporal yield stability in Ethiopia across three survey waves (2011 to 2015) for four selected crops (a) and location of surveyed households in the four most populated regions and present in all three waves 1 to 3 and after filtering (b).

For the longitudinal analysis, we filtered livestock-only households from the sample (due to data constraints) so that it only contains crop-growing and mixed crop-livestock households present for all three waves. Hence, three of the regions had very few households. the number of households per kebele was no longer ten as per the sample design, but instead averaged six households per kebele. The sample sizes for each part of the analysis, following filtering, are illustrated in Fig. 2.



145  
146  
147  
148

Fig. 2: Sample filtering and resulting sample size for each part of the study. It was necessary to filter households primarily to remove those that did not participate in agricultural activities, or that did not harvest any of the major 23 crops in all waves.

149 **Climate data**

150 For precipitation, we used CHIRPS with daily precipitation data from 1981 to present at a 0.05 degrees  
151 resolution grid (Funk et al. 2015). We also used the Climate Research Unit's climate dataset, CRU TS  
152 v4.05, which has monthly observations from 1901 to 2020 of both precipitation and temperature at a  
153 0.5 degrees resolution (Harris et al. 2020). This climate data was extracted at geographic locations  
154 closest to the anonymized GPS coordinates provided in the household survey data.

155

156 We calculate climate variability using the coefficient of variation (CV) of precipitation and temperature  
157 measures commonly used to capture climate variability in agriculture. We considered two different  
158 time periods for these measures. Firstly, short-term month-to-month variability was calculated from  
159 monthly temperature and rainfall in the year prior to the survey year, to capture climate  
160 characteristics in the most recent season. Secondly, long-term annual variability was calculated using  
161 mean annual temperature and total annual rainfall, in the 30-year time period prior to the survey year.  
162 We initially considered additional climate variability measures but have not included in the results due  
163 to their high collinearity with 30-year climate variability. These measures were 10-year climate  
164 variability, annual variability of the long rainy season only (June – Sept), and annual variability of the  
165 short rainy season only (Feb – May).

166

167 We also calculated the Standardized Precipitation-Evapotranspiration Index (SPEI) for September in  
168 the year of each survey using the CRU dataset (Beguería et al. 2014). As the index uses both  
169 temperature and precipitation in its derivation, we used the CRU data for both the precipitation and  
170 temperature. This was calculated on a 3-month timescale from July to September. September is the  
171 last month of the long rainy season, which corresponds to the Meher season (Temam et al. 2019).  
172 From this, we derived a drought index by the number of times in the past 10 years that SPEI was less  
173 than -1.28, following Bozzola and Smale (2020). Positive SPEI values indicate water excess and  
174 negative SPEI values indicate water deficiency. The value -1.28 indicates severe drought events by  
175 approximately corresponding to the lower 10% tail of the SPEI probability distribution function. Based  
176 on this index, 7% of wave 4 households had no droughts, 82% had one drought, and 11% had two  
177 droughts in the long rainy season during the past 10 years. These are potentially from the major  
178 2011/12 and 2015/16 droughts in Ethiopia (Funk et al. 2019).

179

180 **Farm diversity**

181 Diversity was captured in several ways. Species richness was defined for crops by the number of  
182 different species planted by the household in the latest cropping season, and for livestock by the  
183 number of different types owned by the household in the past 12 months. The livestock types included  
184 cattle, goat, sheep, camel, equine, chicken, and bee. Farm richness was derived as the sum of crop  
185 and livestock richness. From these richness measures, we also derived a farm specialization variable.  
186 Households with zero livestock richness were classified as crop-only, households with zero crop  
187 richness were classified as livestock-only, and the rest were classified as mixed.

188

189 Although richness measures are the simplest measures for diversity, they do not account for  
190 differences in field area usage, and thus implicitly assume equal importance of each species in a  
191 household's farming activities. We incorporated land usage using the effective diversity indices. For a  
192 household with  $n$  unique crops, let  $p_i$  be the proportion of cultivated land for crop  $i \in \{1, \dots, n\}$ . The  
193 Shannon diversity index provides a measure of crop evenness, the degree to which all cultivated  
194 species are equally abundant (Shannon 1948). It is given by,

$$195 \quad - \sum_{i=1}^n p_i \ln p_i$$

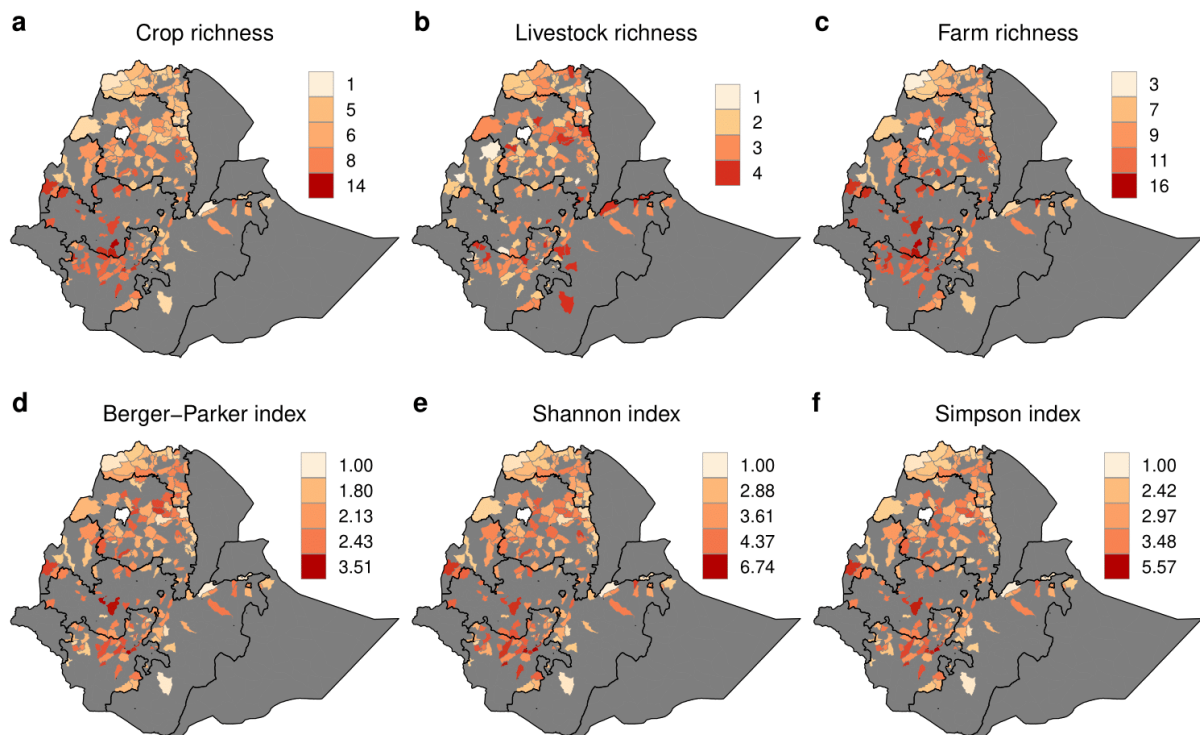
196 The Simpson diversity index provides a measure of crop dominance, the degree to which a small  
197 subset of crop species takes up most of the cultivated area (Simpson 1949). It is given by,

$$198 \quad \sum_{i=1}^n p_i^2$$

199 Finally, as a simple measure of land use diversity, we calculated the Berger-Parker diversity index,  
200 given by  $\max p_i$ , which is simply proportion of cultivated land of the dominant crop. Although this  
201 measure is biased towards species richness, it has the advantage of being more easily interpreted.  
202 Following Jost (2006), these three measures were transformed to get the effective diversity, which  
203 has more desirable properties compared to the raw measures. Most diversity measures for the  
204 households included in waves 1 to 3 tend to be highest in the south-west of Ethiopia (Fig. 3).

205





206

207 *Fig. 3: Spatial distribution of effective diversity measures for the filtered households surveyed in waves 1 to 3. They are*  
 208 *represented here as median diversity at the district level - Ethiopia's third largest administrative division after region and*  
 209 *zone.*

210

## 211 **Temporal yield stability**

212 Caloric yield was used as a measure of average household-level crop yield. Twenty-three crops were  
 213 used to derive caloric yield; these were maize, sorghum, teff, wheat, barley, millet, oats, rice, linseed,  
 214 ground nuts, nugg, rapeseed, sesame, sunflower, fenugreek, horse beans, haricot beans, field peas,  
 215 chick peas, lentils, vetch, white lupin (locally called “gibto”), and soya beans. These crops were  
 216 selected because they were the most comparable across waves; data collection differences made  
 217 other crops unreliable for comparison across waves. To calculate a total yield across all crops, yields  
 218 were converted to caloric yield using caloric content (FAO 2001) and aggregated from field to  
 219 household level via an area-weighted mean. Specifically, for a given household  $h$  in wave  $t$  with crops  
 220  $i$ , the area-weighted mean caloric yield  $Y_{h,t}$ , is given by,

$$221 \quad Y_{h,t} = \frac{\sum_i \text{kcal}_i \times \text{harvest}_i}{\sum_i \text{area}_i}$$

222

223 There is a multitude of yield stability measures defined in the literature, of which we chose six to use  
 224 in our analysis. A detailed theoretical background on stability analysis is given the separately  
 225 (Supplementary Information S11), which highlights why it is important to consider several alternative

226 measures in yield stability analyses. The yield stability measure most commonly used in the literature,  
 227 and thus considered in this study, is the inverse CV  $S_h$ . It is given by,

$$228 \quad S_h = \frac{\mu_h}{\sigma_h}$$

229 *Equation 1*

230 where  $\mu_h$  is the temporal mean and  $\sigma_h$  is the temporal standard deviation of caloric yield of household  
 231  $h$ . Dividing by the mean gives the variability per unit of yield. Taking the inverse is merely to change  
 232 interpretation from instability to stability. In addition to this measure, we implemented the alternative  
 233 CV  $S_h$ , given by,

$$234 \quad S_h = \sqrt{\exp \sigma_h^* - 1}$$

235 where  $\sigma_h^*$  is the standard deviation of the log-transformed yields for each wave. This is more  
 236 appropriate for variables following a log-normal distribution, as might be the case with caloric yield.  
 237 To control for the effect of any yield trend over time, another two stability measures were created by  
 238 detrending the CV with respect to the household's temporal trend, as well as the temporal trend of  
 239 the kebele in which the household is situated. These were derived similarly to Equation 1, but instead  
 240 using a standard deviation of the residuals of a simple linear regression fit of the yield over time. We  
 241 also calculated a stability measure based on power law residuals, as proposed by Döring et al. (2015),  
 242 albeit in the context of the single-species yield. This measure sets a household's stability equal to its  
 243 residual in the power model of yield variance on yield mean for all households, which reduces to,

$$244 \quad \log(\sigma_h^2) = \alpha \log(\mu_h) + \beta$$

245 This is essentially a measure of deviation from the conditional mean yield of all households. Finally,  
 246 we implemented a proportional variability index, given in our case by,

$$247 \quad S_h = 1 - \frac{1}{3} \left( \frac{\min(Y_{h,1}, Y_{h,2})}{\max(Y_{h,1}, Y_{h,2})} + \frac{\min(Y_{h,2}, Y_{h,3})}{\max(Y_{h,2}, Y_{h,3})} + \frac{\min(Y_{h,1}, Y_{h,3})}{\max(Y_{h,1}, Y_{h,3})} \right)$$

248 which is a non-parametric alternative to the CV for yield stability (Heath 2006). This has the advantage  
 249 of not being heavily skewed, and ranging between 0 and 1.

250

## 251 **Statistical modeling**

252 For each analysis, we used a mixed effects model with a random effect for kebele. Survey data tends  
 253 to exhibit at least one level of clustering, based on the response variable (Rabe-Hesketh and Skrondal  
 254 2006). Ethiopian kebeles, being the smallest administrative division, are subject to similar exogenous  
 255 factors. By using a mixed effects model with a kebele-level random effect, the within-kebele  
 256 heterogeneity can be distinguished from the between-kebele heterogeneity, allowing us to determine  
 257 whether kebeles respond in similar ways to exogenous factors such as climate variability. Although

258 higher administrative divisions were also considered for random effects in a nested multi-level  
259 structure, the intra-class correlations were extremely low for these levels, and they were thus omitted.  
260 All models were implemented in R v4.1.3 (R Core Team 2020) using the lme4 package (Bates et al.  
261 2015).

262

## 263 **1.1 Climate variability and diversification**

264 For the cross-sectional analysis, we used a generalized linear mixed effects model with a random effect  
265 for kebele (Equation 2). Farm richness was modeled as Poisson-distributed, with precipitation and  
266 temperature variability as predictors. Temperature and precipitation are not independent predictors,  
267 but are inherently statistically associated (Table A3 in the Appendix). We do not remove one or the  
268 other from the model as they have different relevance for agriculture and differ in the magnitude and  
269 direction of effect on agriculture. In addition, an indicator variable was created to distinguish some  
270 high-leverage Somali households located in areas with extreme precipitation variability. A separate  
271 model was fitted to mixed, crop-only and livestock-only households, as well as a model for all  
272 households pooled together. The variables used in this model are summarized in Table A1 in the  
273 Appendix.

274

$$\begin{aligned} \text{Farm richness}_h | \epsilon_k &\sim \text{Poisson}\left(e^{\beta^T x_h + \epsilon_k}\right) \\ \epsilon_k &\sim N(0, \sigma_K^2) \end{aligned}$$

276

277

*Equation 2*

278

279 To test the hypothesis that diversity is low in the extremes of climate variability, we used quadratic  
280 polynomials of climate variability as predictors. Where a variable's quadratic term has a significant  
281 and negative parameter estimate, the log-mean of farm richness is sufficiently modelled by an  
282 inverted parabola, which has a single peak. We analytically optimized those parameter estimates to  
283 determine the precise climate variability at which diversity is highest. If this peak occurs at a non-  
284 extreme climate variability, as determined by a percentile range, then diversity is lower at the  
285 extremes of climate variability in the observed data and the hypothesis is supported. A disadvantage  
286 of this methodology is that quadratics are symmetric about the peak, which may lead to under-fitting  
287 of a more complex relationship. Although other models such as splines may better capture a non-  
288 linear relationship, this would likely be limited by the availability of accurate climate data.

289

290 To determine whether the proportion of livestock-only households increases as climate variability  
291 increases, we implemented a mixed effects logistic regression model with the climate variability

measures as fixed effects, and kebele as a random effect (Equation 3). For the predictors that give significant and positive parameter estimates, the model supports the hypothesis that the proportion of livestock-only households increases as climate variability increases. The indicator for the high-leverage households used in the previous model was similarly used in this model.

296

$$\text{logit } \mathbb{P}(\text{Livestock oriented}_h) | \epsilon_k, \epsilon_r = \beta^T x_h + \epsilon_k + \epsilon_r$$

$$\epsilon_k \sim N(0, \sigma_K^2)$$

$$\epsilon_r \sim N(0, \sigma_R^2)$$

300

*Equation 3*

301

### 302 **Temporal yield stability**

303 Similar to the cross-sectional analysis, temporal yield stability was modelled using a mixed effects  
 304 model with a random effect for kebele (Equation 4). However, this model considered all available  
 305 predictors as fixed effects (Table A4 in the Appendix), using variable selection procedures to reduce  
 306 model size. An interaction between the diversity variable and log-transformed field area was added  
 307 to examine the relationship between these variables. Exploratory analysis did not reveal large  
 308 differences in slope or intercept estimates among groups, so no additional random effects were  
 309 added. All numeric predictors were scaled and centred. To normalize residuals, the response variable  
 310 was Box-Cox transformed, where the power parameter was calculated using the full model with  
 311 kebele instead treated as a fixed effect. For robustness, we fit the same model to all six of our stability  
 312 measures. The following results and discussion pertain only to the model which uses stability  
 313 measured by Equation 1 – the inverse CV of caloric yield. This measure resulted in the most ideal  
 314 diagnostics including normally-distributed and heteroscedastic residuals. It is also the more commonly  
 315 used measure in the literature, which can aid with interpretability. The results for the models using  
 316 the other stability measures are reported separately (Supplementary Information S1-6).

317

$$\text{Stability}_h | \alpha_k, \epsilon_h = \beta^T x_h + \alpha_k + \epsilon_h$$

$$\alpha_k \sim N(0, \sigma_K^2)$$

$$\epsilon_h \sim N(0, \sigma^2)$$

321

*Equation 4*

322

323 Variable selection first involved developing a list of potential drivers of yield stability. We then  
 324 manually inspected and eliminated variables with extreme collinearity or extreme imbalance. This was  
 325 followed by backwards elimination using Akaike Information Criterion penalty. During backwards

326 elimination, several variables were exempt from elimination for conditioning or for interest in the  
327 study. Namely, we retained agro-ecological zone, region, dominant crop, diversity variables, irrigation,  
328 fertilizer usage, and pesticide usage. Fertilizer usage was measured as the proportion of applied area,  
329 whereas irrigation and pesticide were measured as binary indicators of their usage on any field since  
330 the proportion of applied area for irrigation and pesticide was extremely skewed. After variable  
331 selection, 20 predictors remained in total.

332

333 The yield stability measures were derived at the household-level and encompassed all waves, whereas  
334 the predictors were often defined at lower levels and were wave-specific. This is a case of the micro-  
335 macro problem, whereby the response variable is not on the lowest level of analysis. Although  
336 predictors at the household-level and above can be handled by the usual mixed effects model  
337 framework, predictors at lower levels require further consideration. Therefore, we aggregated plot-  
338 level and field-level predictors to the household-level via area-weighted sums for continuous  
339 variables, indicators for binary variables, and most common values for categorical variables. Following  
340 this, we aggregated time-varying predictors across the three waves via the arithmetic mean for  
341 continuous variables, and most common values for binary and categorical variables. Temporal  
342 aggregation in this manner limits the ability to distinguish household heterogeneity. However, this  
343 trade-off was necessary to analyse stability, a temporal phenomenon, using only three waves.  
344 Furthermore, aggregating via simple means results in similar statistical performance to more complex  
345 methods (Foster-Johnson and Kromrey 2018).

346

347 Due to the collinearity of the diversity variables, they were used separately in three distinct models  
348 rather than combined into a single model. Collinearity of the other variables was not a problem,  
349 indicated by variance inflation factors lower than two for each variable. Farm richness, Shannon  
350 diversity, and Berger-Parker diversity were chosen for continued analysis, and the results and  
351 discussion pertain only to the three models using these variables. The variables used in the models  
352 are summarized in Table A2 in the Appendix. The results for the models using the other diversification  
353 measures are reported separately (Supplementary Information S1-6).

354

## 355 **Results**

### 356 **Climate variability and diversification**

357 We observed the following characteristics of smallholder diversity in this part of the analysis using the  
358 wave 4 household survey for 2018/2019. Livestock-only households, making up 16% of all surveyed

359 households, are dominated primarily by goat-herders. Mixed households, which make up 74% of all  
360 households, tend to favor cattle herding, and most often have maize, teff, or sorghum as their  
361 dominant crop by area. Crop-only households, which make up the remaining 10% of all households,  
362 most often have maize, coffee or sorghum as their dominant crop by area. This minority of households  
363 also tends to have lower crop diversity than mixed households, indicating that the tendency to  
364 specialize by way of only crop-farming is perhaps associated with the tendency to specialize within the  
365 cropping activities. Conversely, diversification by the ownership of livestock is perhaps coupled with  
366 diversification within cropping activities. Among the households that cultivate crops, 11% reported  
367 having only one crop. This behaviour is more likely for crop-only households, and results in a Shannon  
368 diversity and Simpson diversity of one for those households. Farm diversity differs geographically,  
369 where the Southern Nations, Nationalities, and Peoples' Region, Amhara, and Benchsangul Gumuz  
370 were the three regions with the highest diversity. The former had an average Shannon diversity of  
371 3.69, which is equivalent to 3.69 equally abundant crops on the average farm in this region. As  
372 expected, the two regions that are primarily livestock-only, Afar and Somali, also had the lowest  
373 diversity.

374

375 Climate variability significantly affects farm richness for both mixed and specialized (crop- or livestock-  
376 only) farm types. Specifically, results from the farm richness models (Equation 2) indicated that climate  
377 variability predictors were statistically significant in the linear term<sup>1</sup> for all but the livestock-only  
378 model's annual rain variability (Table 1). For the pooled, mixed and crop-only household models, rain  
379 variability was negatively associated with farm richness and temperature variability was positively  
380 associated with farm richness. This holds for both month-to-month and annual variability. The  
381 livestock-only model showed the opposite trends, with households in areas with higher rain variability  
382 predicted to have higher diversity, and households in lower temperature variability predicted to have  
383 higher diversity. Climate variability explained 27% of the spatial variance in farm richness among  
384 households. This was derived by pseudo- $R^2$  measures (Nakagawa and Schielzeth 2013). The variance  
385 explained was significantly lower for the mixed ( $R^2 = 0.13$ ), crop-only ( $R^2 = 0.19$ ), and livestock-only  
386 models ( $R^2 = 0.16$ ). When also considering the kebele random effect, 58% of variance in farm

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<sup>1</sup> As polynomial terms are only approximately orthogonal in Poisson mixed effects models, this is not necessarily indicative of the linear model with non-significant quadratic terms removed. To ensure model outcomes were similar, we refit the models with the non-significant quadratic terms removed. Statistical significance of  $p < 0.05$  was maintained and signs of the estimates were the same for all but annual rain CV in the crop-only model. These results are reported separately (Supplementary Information S7-10).

387 richness was explained for the pooled model, with a decrease for the mixed ( $R^2 = 0.42$ ), crop-only  
 388 ( $R^2 = 0.38$ ), and livestock-only models ( $R^2 = 0.25$ ).

389

Predictors	Pooled		Mixed		Crop-only		Livestock-only	
	Log-Mean (SE)	p-value	Log-Mean (SE)	p-value	Log-Mean (SE)	p-value	Log-Mean (SE)	p-value
Intercept	1.76 (0.02)	***	1.99 (0.02)	***	1.21 (0.05)	***	0.94 (0.05)	***
Month-to-month rain CV	-4.69 (1.71)	***	-3.99 (1.25)	***	-3.83 (1.27)	***	3.48 (1.19)	***
Month-to-month rain CV <sup>2</sup>	2.61 (1.37)	*	1.47 (1.07)		2.06 (0.99)	**	-0.80 (1.07)	
Annual rain CV	-12.43 (2.00)	***	-3.00 (1.45)	**	-2.45 (1.23)	**	-0.13 (1.30)	
Annual rain CV <sup>2</sup>	-1.87 (1.87)		-0.55 (1.56)		-0.93 (0.88)		-1.50 (1.29)	
Month-to-month temp. CV	4.90 (1.72)	***	2.79 (1.36)	**	2.56 (1.26)	**	-2.93 (1.20)	**
Month-to-month temp. CV <sup>2</sup>	1.86 (1.44)		0.97 (1.05)		-0.48 (0.96)		-1.67 (1.22)	
Annual temp. CV	8.90 (1.52)	***	5.70 (1.03)	***	1.83 (0.86)	**	-6.56 (1.46)	***
Annual temp. CV <sup>2</sup>	-1.20 (1.54)		-1.82 (1.00)	*	-1.25 (0.75)	*	0.52 (1.51)	
<i>Random Effects</i>								
$\sigma^2$	0.16		0.13		0.26		0.35	
$\sigma_K^2$	0.12		0.07		0.08		0.04	
ICC	0.42		0.34		0.24		0.10	
Marginal R <sup>2</sup>	0.272		0.132		0.192		0.162	
Conditional R <sup>2</sup>	0.581		0.424		0.382		0.246	

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1, blank = not significant

390 *Table 1: Results of the Poisson mixed effects model for the relationship between climate variability and farm richness.*

391

392 In some cases, we observed non-linear relationships between climate variability and (log-)mean  
 393 diversity that is indicative of a modeled peak value for farm richness. Negative quadratic parameter  
 394 estimates were observed for annual temperature variability in the mixed and crop-only household  
 395 models, albeit at the 0.1 significance level (Table 1). This suggests that there exists a certain annual  
 396 temperature variability where diversity is highest. However, the maximum diversity predicted by the  
 397 modelled polynomial was beyond the 90th percentile of the observed data, at a CV of ~0.027 and  
 398 ~0.024 for the mixed and crop-only household models respectively (Figure A1 in the Appendix). Hence,  
 399 for crop-only and mixed households, this result means that diversity is highest at high annual  
 400 temperature variability, and lowest at low annual temperature variability, with no peak in the middle  
 401 of the range.

402

403 The logistic regression model for livestock-only farms (Equation 3 **Erreur ! Source du renvoi**  
404 **introuvable.**) showed that these farms are more common in regions with high annual rainfall  
405 variability. The model also had significant parameter estimates for temperature variability (Table 2).  
406 The negative estimate for annual temperature variability implies that livestock-oriented farms  
407 become less common in climates with greater annual temperature variability. This conversely suggests  
408 that they become more common in climates with a lower mean annual temperature due to the  
409 negative correlation between temperature's variability and mean (Spearman's  $\rho = -0.81, p <$   
410  $0.001$ ) (Table A3). The model also had a high intra-class correlation ( $ICC = 0.77$ ) that is dominated  
411 by the variance attributable to between-kebele differences. This means that the propensity for a  
412 household to be livestock-oriented appears to be more dependent on the kebele than to the fixed  
413 effects or the region. The high intra-class correlation is reflected in the model's conditional explained  
414 variance (conditional  $R^2 = 0.87$ ), which is significantly lower when kebele isn't taken into account  
415 (marginal  $R^2 = 0.44$ ).  
416

Predictors	Pooled	
	Estimate (SE)	p-value
Intercept	-4.92 (0.73)	***
Month-to-month rain CV	1.06 (0.59)	*
Annual rain CV	2.58 (0.66)	***
Month-to-month temp. CV	-1.23 (0.44)	***
Annual temp. CV	-1.72 (0.50)	***
<i>Random Effects</i>		
$\sigma^2$	3.29	
$\sigma_K^2$	9.76	
$\sigma_R^2$	1.41	
ICC	0.770	
Marginal $R^2$	0.436	
Conditional $R^2$	0.872	

\*\*\*p<0.01, \*\*p<0.05, \*p<0.1

417 *Table 2: Results of the logistic regression mixed effects model for livestock-only farm presence.*  
418

## 419 **Temporal yield stability**

420 Temporal yield stability between 2011 and 2015 in Ethiopia had a median of 1.76. To give an example  
421 of this, a household with a stability of 1.76, or equivalently an inverse CV of  $1.76^{-1} = 0.57$ , could have  
422 a mean caloric yield in 1 year that was similar to its average over the three waves, with the other 2  
423 years having a caloric mean yield 43% higher and 43% lower than the average. There are also marked

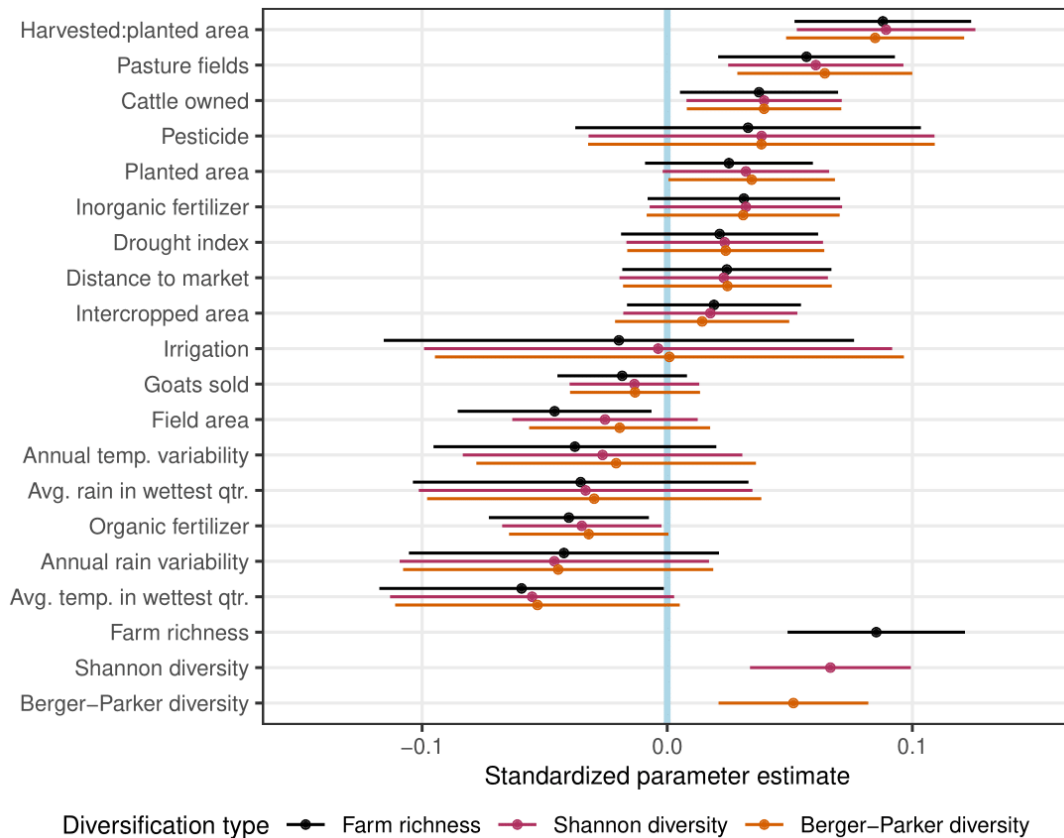


424 regional differences in typical stability. Temporal yield stability was typically highest among  
425 households in Benshangul Gumuz and Amhara, with a median yield stability of 2.43 and 1.99  
426 respectively. Benshangul Gumuz is a sub-humid region in the Western Ethiopian lowlands with  
427 primarily maize/sorghum mixed systems. The least stable regions were Dire Dawa and the Southern  
428 Nations, Nationalities, and Peoples' Region, with a median yield of 1.20 and 1.53 respectively. Dire  
429 Dawa is a small semi-arid region in the lowlands of Eastern Ethiopia. All households in this region had  
430 sorghum as their dominant crop. Oromiya had the largest range of stability values, from 0.61 to 56.1,  
431 possibly due to its greater geographical extent and sample size. Furthermore, households in sub-  
432 humid climates were more stable than households in humid and semi-arid climates, where the median  
433 yield stability was 1.90 for the former, and 1.69 and 1.65 for the latter two respectively. All  
434 aforementioned descriptive results hold when considering mean, instead of median, as the measure  
435 of central tendency.

436

437 Model results for the yield stability analysis (Equation 4) show that farm richness and Shannon  
438 diversity were significant positive predictors of stability ( $p < 0.01$ , Fig. 4, Table A5 in the Appendix).  
439 The estimate for Berger-Parker diversity was also positive and significant ( $p < 0.01$ ), indicating that  
440 households which dedicate a higher proportion of crop area to the dominant crop species tend to  
441 have lower overall yield stability. This result generally held true when introducing an interaction effect  
442 between this variable and the dominant crop type. This indicates that the effect of Berger-Parker  
443 diversity is not just a function of characteristics of specific crops. Only for perennials as the dominant  
444 crop type did the effect of the Berger-Parker diversity on yield stability become negative. Crop richness  
445 and Simpson diversity gave similarly positive and significant parameter estimates to the models  
446 presented here, although livestock richness was a poor predictor for caloric yield stability both in  
447 isolation and when coupled with crop richness (Supplementary Information S1-6). Finally, the  
448 interaction between diversity and field area was not significant at the 0.05 significance level, although  
449 it was significant at the 0.1 level for the farm richness model. This model had a significant negative  
450 parameter estimate for field area, although it was smaller in magnitude than the effect of farm  
451 richness.

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Fig. 4: Results of mixed effects model for three temporal yield stability models with different diversity measures. Dots represent parameter point estimates and lines represent 95% confidence intervals. Significant parameter estimates are those with confidence intervals that are non-overlapping with the vertical zero line.

Parameter estimates for non-diversity predictors were mostly similar across the three models (Fig. 4, Table A5 in the Appendix). The strongest non-diversity predictor of household yield stability was the proportion of harvested area to planted area, which was statistically significant and similar in magnitude to the effect of farm richness. The number of pasture fields was also statistically significant and positively associated with stability, as was cattle headcount albeit to a lesser extent. The proportion of area with organic fertilizer was negatively associated with stability, although not at the 0.05 significance level for one of the models. At the 0.1 level, the average temperature in the wettest quarter was the strongest negative predictor of stability. The region and dominant crop conditioning variables were significant at the 0.05 level. Intra-class correlation was low, at about 18% for all models, so stability can be quite different for households within the same kebele (Table A5 in the Appendix). The explained variance was similar for all models, with a marginal and conditional pseudo- $R^2$  of 0.157 and 0.315 respectively for the farm richness model. Models using the other stability measures performed similarly (Supplementary Information S1-6).

## 472 **2 Discussion**

### 473 **2.1 Climate variability and diversification**

474 We expected diversity to be low when climate variability is either very high or very low. This is because  
475 i) highly variable climates may limit growth and development of a number of crops (Waha et al. 2018)  
476 making high crop richness less economically viable, and ii) low variability could be more supportive of  
477 intensive monocropped farming systems (Howden et al. 2010). We find here that only climate  
478 variables taken together conform to the hypothesis. Diversity is generally lowest when precipitation  
479 variability is high and when temperature variability is low. Due to the strong negative correlation  
480 between annual temperature variability and annual mean temperature (Table A3 in the Appendix),  
481 the results also suggest that diversity is lower in warmer areas. This opposes the findings of Ochieng  
482 et al. (2020) in rural Kenyan households, which found that diversification is more widespread in  
483 warmer climates.

484

485 There are two possible explanations for this result. Firstly, the results of the logistic regression model  
486 showed that pastoralism is more prevalent in warmer areas with low annual temperature variability  
487 (Table 2). Hence, the lower diversity that is observed at the lower end of temperature variability may  
488 in fact be due to the higher frequency of livestock-oriented households, which have a low diversity  
489 overall. Secondly, the result could be explained by the characteristics of precipitation in areas with  
490 low annual temperature variability, where temperature variability is positively correlated with  
491 precipitation (Table A3 in the Appendix). Past studies show that bioclimatic variables related to  
492 precipitation were most important in Ethiopian land suitability simulations (Evangelista et al. 2013).  
493 Moreover, precipitation was often a more important factor than temperature for crop land suitability  
494 in Ghana (Chemura et al. 2020). Hence, the low diversity in areas with low temperature variability  
495 could be due to the more pervasive effects of low precipitation. Due to the limitations of observational  
496 data, any conclusions as to the causality or relative importance of either factor would need to come  
497 from external sources, such as field experiments.

498

499 An important caveat regarding interpretation of the month-to-month climate variability results is that  
500 our measure is not the average variability within all years – it is only the monthly variability that was  
501 observed in the year prior to the year of the surveys. In this context, we can consider two possible  
502 household response types to climate variability: an adaptation response to persistently high  
503 variability, and a reactionary response to recently high variability. The former is more likely captured  
504 with our measure of annual variability derived from the past 30 years. However, the latter cannot be

505 captured with our measure of month-to-month variability in the past year. The month-to-month  
506 measure only allows us to compare recent variability between households, rather than comparing a  
507 household's recent variability to its norm. By keeping this in mind, we can put our results for this part  
508 of the study into the proper context.

509

## 510 **Temporal yield stability**

511 Our results show a general positive association between diversity and temporal yield stability. This  
512 aligns with theoretical and observational arguments from the literature suggesting that crop  
513 diversification can lead to more stable yields (Tilman et al. 1998; Urruty et al. 2016; Liu et al. 2019;  
514 Renard and Tilman 2019; Hufnagel et al. 2020). The effect of crop area distribution on stability is less  
515 often studied, so the observed significant positive effect of Shannon diversity is an informative  
516 outcome. Moreover, the positive effect of Berger-Parker diversity, albeit lower in magnitude than  
517 Shannon diversity, suggests that the area of the dominant crop is an important factor for yield stability,  
518 supporting the findings of Mahaut et al. (2021). As for the random effect for kebele, the models' low  
519 intraclass correlation means that households within the same kebele do not have similar stability  
520 relative to households from other kebeles. This is surprising since yield stability is very likely  
521 dependent on exogenous factors, such as weather shocks, which are essentially equal among all  
522 households within a kebele but highly varied between kebeles. It is possible that this is due to including  
523 region and agro-ecological zone as conditioning variables in the models, which might to some extent  
524 negate the effect of exogenous variables. Nevertheless, the overall effect of diversity on temporal  
525 yield stability is clear in our results, which suggests that it may be an important factor in achieving  
526 food system stability.

527

528 Several unexpected effects were observed in the yield stability model. Firstly, irrigation and inorganic  
529 fertilizer usage were not significant determinants of stability, and organic fertilizer was a negative  
530 determinant of stability. This is despite evidence that both irrigation and fertilizer use have a positive  
531 effect on both yield and yield stability (Sánchez 2010; Knapp and van der Heijden 2018; Renard and  
532 Tilman 2019; Egli et al. 2021). To account for potential interaction between these variables and  
533 droughts, which may affect the efficacy of irrigation and fertilizer, we also tested the model with these  
534 interaction terms included, but the results were similar. Not observing any effect in our models may  
535 be a result of diluting the variables when temporally aggregating during data preprocessing, as we had  
536 to create one variable from each time-varying variable per household from the data over all three  
537 waves. Recall bias could have also influenced the reporting on agricultural inputs (Dillon et al. 2021).  
538 Secondly, the drought index had a positive effect on stability, although it was not a significant effect.

539 This would imply that households with a more frequent past occurrence of droughts are also more  
540 stable. One possible explanation for this is that the likelihood of droughts itself acts as a driver for  
541 adaptation measures. This is supported by findings that past climate shocks is a positive predictor of  
542 diversification in Namibian households (Mulwa and Visser 2020). As a result, there is an increased  
543 adaptive capacity among farms in areas that have experienced droughts in the past decade, and the  
544 overall stability for these households may benefit from this even during times without drought. This  
545 explanation is not examined further in this study but stands as an avenue for future work.

546

547 The role of livestock in yield stability may require a more complex approach than that taken here.  
548 Literature suggests that livestock production can be more resilient to high climate variability than crop  
549 production (Godde et al. 2021), which may also be inferred from our logistic regression model results  
550 (the “Climate variability and diversification” section). However, our models also showed that the  
551 number of livestock types owned by the household was not associated with yield stability. This could  
552 be because we did not incorporate livestock yield (e.g., meat, milk, eggs) into a single measure of  
553 overall food yield for the household. Thus, the only mechanism by which livestock diversification could  
554 increase yield stability in this model is through the indirect effects of livestock ownership, such as  
555 manure usage for soil fertility, and draught power. Furthermore, the selling of livestock to cope with  
556 shocks is an adaptation strategy which is more likely to be reflected in an income response variable  
557 than a yield response variable. Although our results did not support the implicit hypothesis that  
558 livestock diversification increases yield stability, it is quite possible that consideration of farm stability  
559 as a whole, including livestock production stability, would provide more informative outcomes.

560

561 Future research could investigate the diversity-stability relationship across the broad range of farm  
562 typologies to discover which farm types are best suited to diversification as a stability-enhancing  
563 solution. Similarly, a more crop-centric approach to stability analysis, for example looking at the yield  
564 stability of farms growing specific combinations of crops, may highlight synergistic crop species and  
565 thus help to synthesize conclusions regarding several diversification strategies simultaneously. We  
566 further note that stability as measured here did not consider macro-nutrients or micro-nutrients of  
567 crops. Given that caloric yield stability may differ from protein, carbohydrate and fat stability in terms  
568 of the response to diversification (Egli et al. 2021), as well as the importance of micro-nutrient  
569 availability in food security for subsistence households (Sibhatu et al. 2015), follow-up studies using  
570 this aspect of crop stability are desirable. Finally, to bolster conclusions drawn in this study, we  
571 recommend continued data sharing and collection for ongoing household survey panels with a strong  
572 focus on accuracy and consistency between waves.

573

## 574 **Barriers to implementation**

575 Several barriers can make farm diversification difficult or infeasible for smallholders. Some of these  
576 barriers include an increasingly variable climate, climate change driven changes in land suitability for  
577 crops (Evangelista et al. 2013; Chemura et al. 2020), lack of finance and knowledge (Ochieng et al.  
578 2017), and a lack of investment in research, machinery, and infrastructure (Hufnagel et al. 2020).  
579 Furthermore, the benefits of diversification may not always outweigh the resources required for  
580 smallholders to implement and maintain diversification strategies, such as the financial costs, extra  
581 labor, and knowledge (Rosa-Schleich et al. 2019).

582

583 The extensive review by Lin (2011) describes several other barriers, including a lack of policy  
584 incentives, a disproportionate focus on biotech solutions, and the misconception that monocropped  
585 systems result in far greater yields. This is followed by a proposal of key strategies for overcoming  
586 these barriers, including implementation or improvement of crop and landscape simulation models,  
587 stakeholder-based participatory research, and farm income support systems (Lin 2011). In addition,  
588 access to climate information has been suggested as a strategy for opening up diversification  
589 opportunities by giving households the information needed to strategically attenuate the effects of  
590 climate change (Mulwa and Visser 2020). Our study provides more reason to invest in the  
591 aforementioned strategies to overcome barriers of implementation, thereby giving more smallholders  
592 the option to diversify and stabilize caloric yield.

593

594 When considering the role of diversification as an adaptation strategy for climate variability, it is  
595 important to weigh up any benefits with the possibility of failure under changing climatic conditions,  
596 and to do so in comparison to alternative adaptation strategies. For example, implementing or  
597 improving irrigation systems in areas with high precipitation variability is an alternative adaptation  
598 strategy which is very likely to help smallholders combat droughts and improve agricultural resilience  
599 (Temam et al. 2019). However, even if this is estimated to be a more effective long-term solution, the  
600 adoption of irrigation systems among smallholders is a multifaceted problem that could be far more  
601 difficult to overcome than the challenges of diversification (Asrat and Anteneh 2019). Moreover,  
602 although irrigation can improve stability, irrigation alone may not be enough to counteract climate  
603 variability (Mahaut et al. 2021). Therefore, the decision to diversify needs to balance the trade-off  
604 between risk reduction from climate challenges, the difficulties of choosing the right diversification  
605 strategies, and the economic constraints.

606

## 607 **Conclusion**

608 This study asked several questions on the relationship between farm-level diversity, climate variability,  
609 and temporal yield stability in Ethiopia and for different types of farming households. Our findings  
610 suggests that certain ranges of climate variability could destabilize household crop yield by limiting  
611 diversification opportunities.

612

613 Farm richness is lowest at high precipitation variability, which indicates higher risks for water shortage,  
614 and is maximized at high annual temperature variability in temperate climate zones. For pastoralists,  
615 the trend was opposite, and their prevalence increases with annual precipitation variability, and  
616 decreases with annual and month-to-month temperature variability.

617

618 Temporal yield stability increases with farm richness and crop evenness. This relationship supersedes  
619 the effect of other variables including farm inputs and the distance to markets. However, several  
620 variables do have a strong positive effect on stability, including the proportion of harvested to planted  
621 area and the number of pasture fields. Temporal yield stability has little dependence on locality,  
622 meaning that households in close proximity aren't necessarily going to have similar yield stability.

623

624 These findings indicate that diversification opportunities for crop-growing households are highest in  
625 areas where short- and long-term rainfall variability is not excessively high, and that diversity in many  
626 forms may have a stabilizing effect on crop yields. This suggest that, for rural farming households in  
627 Ethiopia, certain ranges of climate variability could destabilize household crop yield by limiting  
628 diversification opportunities. We expect similar conclusions from other African countries with a  
629 comparable economic and climatic context to Ethiopia, but this requires further testing. There is,  
630 however, a major data challenge in assessing temporal yield stability empirically on the household  
631 level. Yield stability is vital for smallholders in developing countries, where the impact of poor crop  
632 seasons creates major threats to food security. Therefore, we suggest that researchers and policy-  
633 makers consider not only the direct effects of climate change on crop yield, but also its indirect effects  
634 on yield stability caused by increasingly limited adaptation choices.

635

636

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## Appendix

Variable	Pooled (N=2521)				Mixed (N=1859)				Crop-only (N=255)				Livestock-only (N=407)			
	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
Farm richness	6.539	3.798	1.000	24.00	7.795	3.506	2.000	24.00	3.584	2.354	1.000	12.00	2.658	1.417	1.000	6.000
Month-to-month rain CV	1.063	0.279	0.560	1.883	1.036	0.274	0.560	1.883	1.013	0.296	0.560	1.883	1.215	0.237	0.640	1.756
Annual rain CV	0.132	0.044	0.059	0.376	0.121	0.032	0.059	0.376	0.118	0.029	0.059	0.205	0.190	0.054	0.059	0.376
Month-to-month temp. CV	0.072	0.019	0.030	0.110	0.071	0.018	0.033	0.110	0.068	0.019	0.036	0.108	0.077	0.020	0.030	0.108
Annual temp. CV	0.020	0.003	0.009	0.029	0.021	0.003	0.009	0.029	0.020	0.003	0.014	0.029	0.017	0.003	0.009	0.026

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Table A1: Descriptive statistics of variables used in the analysis of diversification and climate variability, disaggregated by farm specialization.

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800

Variable	Description	Summary				
Continuous predictors		Mean	SD	Min.	Median	Max.
Farm richness	Sum of crop species and livestock types	9.728	3.433	1.667	9.333	22.667
Shannon diversity	Crop evenness measure based on proportion of area used by each crop species	3.750	1.364	1.000	3.598	9.148
Berger-Parker diversity	Inverse proportion of the farm's total harvested area under the primary crop	2.204	0.624	1.000	2.163	4.941
Field area	Total field area (ha) of the farm	1.933	4.798	0.021	1.333	143.377
Harvested:planted area	Proportion of harvested area relative to planted area	0.624	0.189	0.001	0.648	1.000
Planted area	Proportion of the farm's total field area planted in the most recent	0.806	0.162	0.231	0.851	1.139
Pasture fields	Number of pasture fields owned by the household	0.897	1.033	0.000	0.667	7.667
Intercropping	Proportion of harvested area that had multiple crops in one plot	0.847	0.224	0.000	0.961	1.000
Inorganic fertilizer	Proportion of cultivated area with inorganic fertilizer applied (urea or DAP)	0.371	0.324	0.000	0.309	1.620
Organic fertilizer	Proportion of cultivated area with organic fertilizer applied (manure, compost, or other)	0.226	0.229	0.000	0.153	1.060
Avg. rain in wettest qtr.	Average total rainfall (mm) in the wettest quarter, based on the past 30 years	629.343	205.820	184.000	595.833	1177.333
Avg. temp. in wettest qtr.	Average monthly temperature (°C) in the wettest quarter, based on the past 30 years	184.193	28.713	106.000	183.000	268.000
Annual rain variability	Coefficient of variation of total annual precipitation (mm), based on the past 30 years	0.119	0.030	0.065	0.113	0.223

Annual temp. variability	Coefficient of variation of average annual temperature ( ° C), based on the past 30 years	0.020	0.003	0.013	0.020	0.028
Drought index	Number of times in the past 10 years the SPEI3 index was below -1.28 in the last month of the Meher season	1.081	0.290	0.333	1.000	1.667
Cattle owned	Number of cattle owned by the household at the time of the survey	4.281	3.640	0.000	3.667	44.333
Goats sold	Number of goats sold by the household in the past 12 months from the survey	0.334	0.792	0.000	0.000	7.667
Distance to market	Distance from household to nearest major market (km)	59.886	39.328	2.900	55.433	221.867
<i>Categorical predictors</i>		<b>Count</b>				
Region	Ethiopia's largest administrative division	8				
Agro-ecological zone	Climatic zone, aggregated to aridity description only	3				
Dominant crop	Crop with the highest planted area in the most recent Meher season	12				
<i>Binary predictors</i>		<b>% True</b>				
Irrigation	Indicates whether irrigation was used on any field	2				
Pesticide	Indicates whether pesticide, herbicide, or fungicide was used on any plot	2				
<i>Response</i>		<b>Mean</b>	<b>SD</b>	<b>Min.</b>	<b>Median</b>	<b>Max.</b>
Stability	Inverse coefficient of variation of crop caloric yield (kcal/ha) over the three survey waves	2.757	3.539	0.612	1.757	56.050

801 *Table A2: Descriptive statistics of variables used in the analysis of temporal yield stability.*

802

	<b>Annual temp. variability</b>	<b>Total annual precipitation</b>	<b>Annual precipitation variability</b>
<b>Mean annual temperature</b>	-0.81, p < 0.001	-0.42, p < 0.001	0.26, p < 0.001
<b>Annual temp. variability</b>	-	0.37, p < 0.001	-0.35, p < 0.001
<b>Total annual precipitation</b>	-	-	-0.84, p < 0.001

803 *Table A3: Spearman's  $\rho$  and significance levels for correlations between 30-year climate variability measures.*

804

<b>Diversification</b>	<b>Farm characteristics</b>	<b>Farm inputs</b>	<b>Livestock</b>	<b>Climate</b>	<b>Location and landscape</b>
Crop richness	Dominant crop	Irrigation usage	Cattle <sup>12345</sup>	Annual rain mean	Region
Livestock richness	Dominant crop harvest	Organic fertilizer usage	Goat <sup>12345</sup>	Annual rain CV	Agro-ecological zone
Farm richness	Dominant crop area	Inorganic fertilizer usage	Sheep <sup>12345</sup>	Annual temp. mean	Elevation
Shannon index	Subdominant crop	Pesticide usage	Camel <sup>12345</sup>	Annual temp. CV	Distance to nearest road
Simpson index	Subdominant crop harvest	Has intercropped plots	Equid <sup>13</sup>	Month-to-month rain mean	Distance to nearest market
Berger-Parker index	Subdominant crop area		Chicken <sup>134</sup>	Month-to-month rain CV	Distance to nearest town

Farm specialization	Field area	Beehive <sup>1</sup>	Month-to-month temp. mean	Topographic wetness index
	Cultivated area		Month-to-month temp. CV	Workability
	Harvested area		Avg. rain in wettest qtr.	Nutrient availability
	Pasture area		Avg. temp. in wettest qtr.	Nutrient retention
	Damaged area		Drought index	Rooting conditions
	Number of fields		SPEI3	Root oxygen availability
	Field steepness		Reported drought	Excess salts
			Reported flood	Toxicity
		Reported heavy rains		

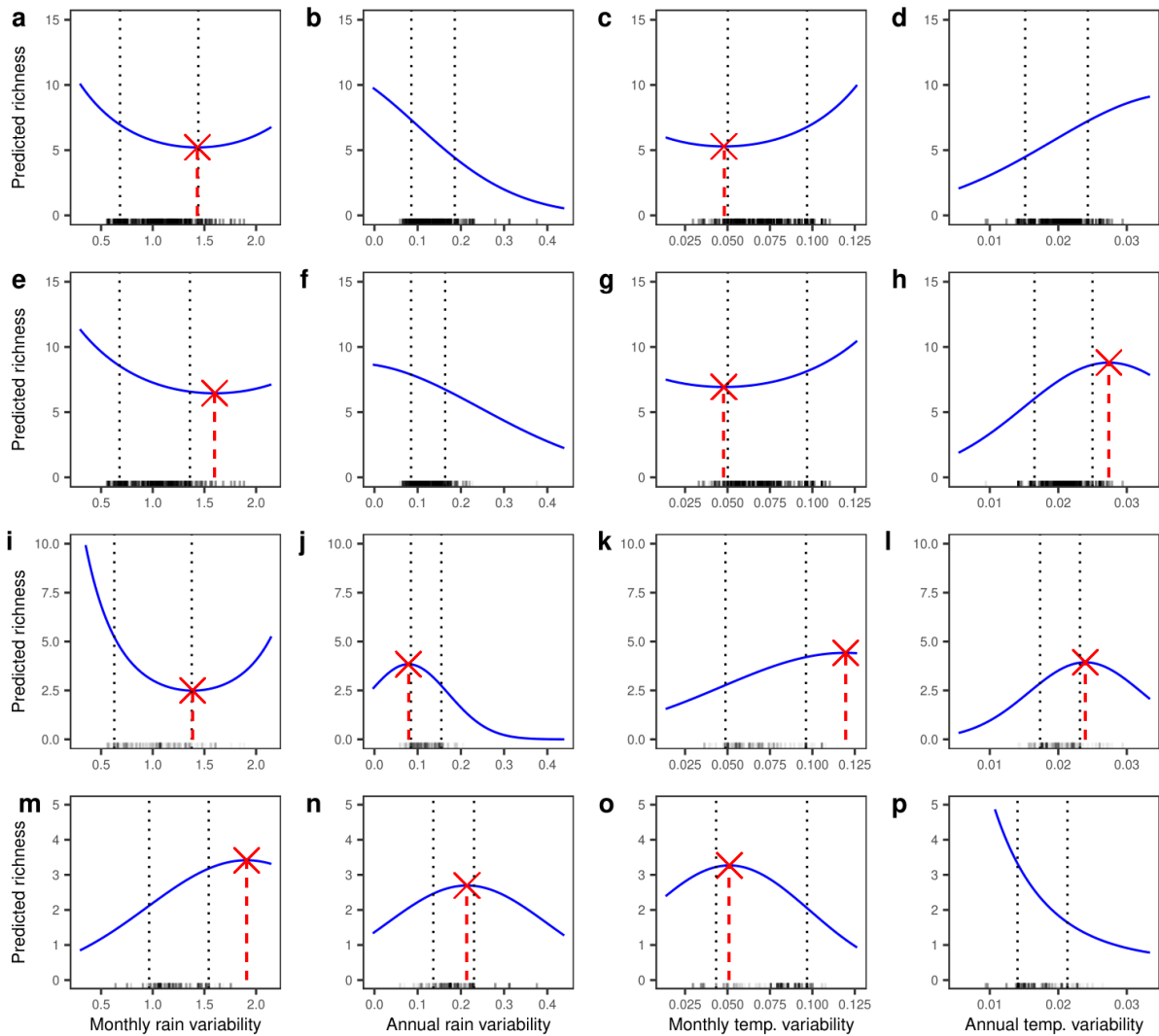
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**Note:** <sup>1</sup>owned, <sup>2</sup>milked, <sup>3</sup>sold, <sup>4</sup>slaughtered, <sup>5</sup>milk yield

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805 *Table A4: Complete list of variables considered for the temporal yield stability model.*

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807  
 808 *Figure A1: Predicted farm richness (blue) for month-to-month rain variability (a,e,i,m), annual rain variability (b,f,j,n), month-*  
 809 *to-month temperature variability (c,g,k,o), and annual temperature variability (d,h,l,p). Turning points are indicated (red)*  
 810 *where applicable. Results are shown for the pooled households model (a,b,c,d), the mixed households model (e,f,g,h), the*  
 811 *crop-only households model (i,j,k,l), and the livestock-only households model (m,n,o,p). Data points are plotted (black), and*  
 812 *vertical dotted lines indicate the 10th and 90th percentiles of the observed data. Please note the different scales used for the*  
 813 *y-axis.*

814

Predictors	Farm richness		Shannon diversity		Berger-Parker diversity	
	Estimate (SE)	p-value	Estimate (SE)	p-value	Estimate (SE)	p-value
Intercept	0.77 (0.09)	***	0.71 (0.09)	***	0.69 (0.09)	***
Irrigation	-0.02 (0.05)		0.00 (0.05)		0.00 (0.05)	
Pesticide	0.03 (0.04)		0.04 (0.04)		0.04 (0.04)	
Organic fertilizer	-0.04 (0.02)	**	-0.03 (0.02)	**	-0.03 (0.02)	*
Inorganic fertilizer	0.03 (0.02)		0.03 (0.02)		0.03 (0.02)	
Intercropped	0.02 (0.02)		0.02 (0.02)		0.01 (0.02)	
Distance to market	0.02 (0.02)		0.02 (0.02)		0.02 (0.02)	



Cattle owned	0.04 (0.02)	**	0.04 (0.02)	**	0.04 (0.02)	**
Goats sold	-0.02 (0.01)		-0.01 (0.01)		-0.01 (0.01)	
Field area	-0.05 (0.02)	**	-0.03 (0.02)		-0.02 (0.02)	
Harvested_planted_ratio	0.09 (0.02)	***	0.09 (0.02)	***	0.08 (0.02)	***
Planted_area	0.03 (0.02)		0.03 (0.02)	*	0.03 (0.02)	**
Pasture_fields	0.06 (0.02)	***	0.06 (0.02)	***	0.06 (0.02)	***
Droughts	0.02 (0.02)		0.02 (0.02)		0.02 (0.02)	
Annual rain variability	-0.04 (0.03)		-0.05 (0.03)		-0.04 (0.03)	
Annual temp. variability	-0.04 (0.03)		-0.03 (0.03)		-0.02 (0.03)	
Avg. rain in wettest qtr.	-0.04 (0.03)		-0.03 (0.03)		-0.03 (0.03)	
Avg. temp in wettest qtr.	-0.06 (0.03)	**	-0.06 (0.03)	*	-0.05 (0.03)	*
Diversity	0.09 (0.02)	***	0.07 (0.02)	***	0.05 (0.02)	***
Diversity × Field area	-0.02 (0.01)	*	-0.01 (0.01)		-0.01 (0.01)	
<i>Conditioning variables</i>						
Region		***		**		**
Agro-ecological zone						
Dominant crop		**		**		**
<i>Random Effects</i>						
$\sigma^2$	0.16		0.16		0.16	
$\sigma_K^2$	0.04		0.04		0.04	
ICC	0.19		0.18		0.18	
Marginal R <sup>2</sup>	0.157		0.153		0.149	
Conditional R <sup>2</sup>	0.315		0.308		0.305	

**Note:** LRT with Satterthwaite approximations. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1, blank = not significant

815 *Table A5: Mixed effects model results for temporal yield stability, with farm richness, Shannon diversity, or Berger-Parker*  
816 *diversity as diversification measures.*