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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 synchronization 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).

109

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).

134

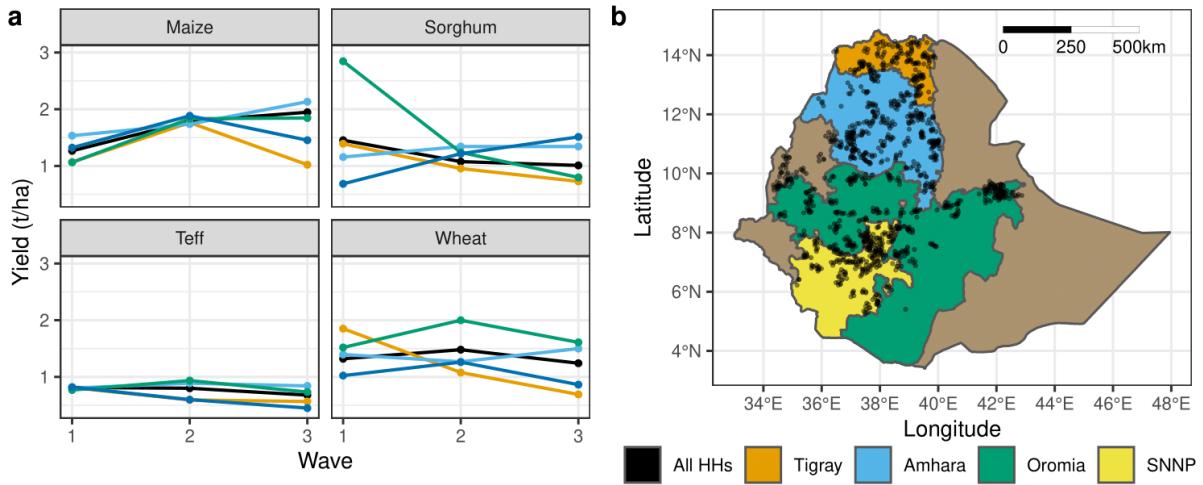


Fig. 1: Temporal yield stability in Ethiopia across three survey waves (2011 to 2015) for four selected crops (a) and location of surveyed households in the four most populated regions and present in all three waves 1 to 3 and after filtering (b).

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.

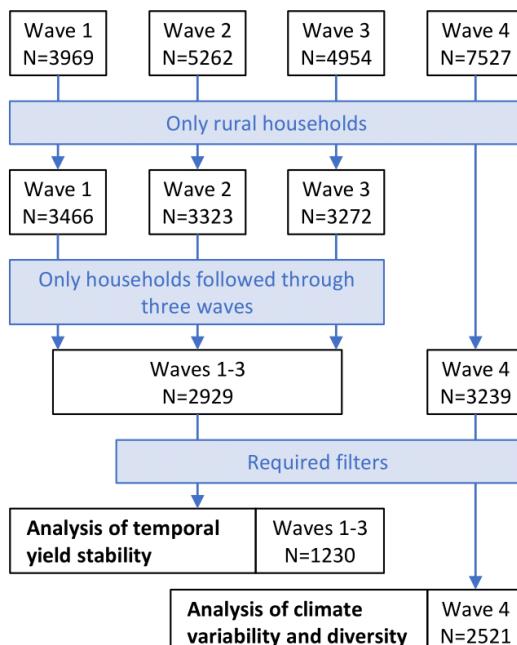


Fig. 2: Sample filtering and resulting sample size for each part of the study. It was necessary to filter households primarily to remove those that did not participate in agricultural activities, or that did not harvest any of the major 23 crops in all waves.

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,

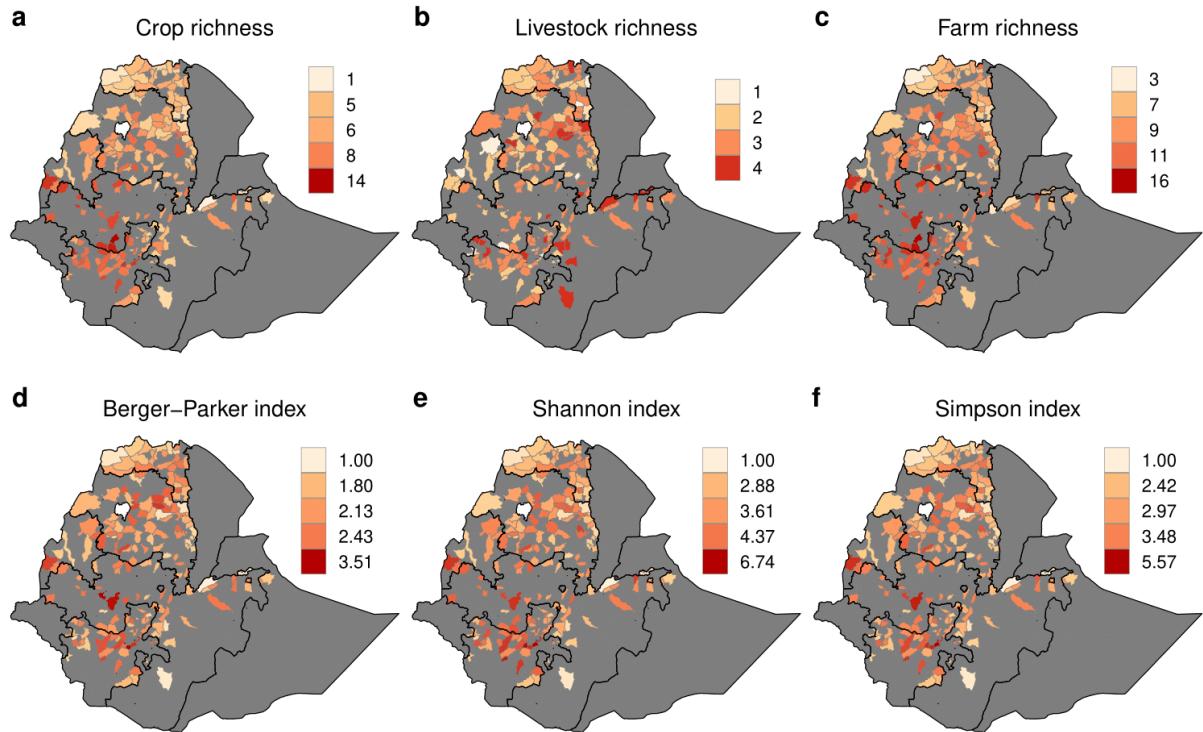
$$195 - \sum_{i=1}^n p_i \ln p_i$$

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,

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

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
208
209
210

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

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, nueg, 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
224
225

There is a multitude of yield stability measures defined in the literature, of which we chose six to use in our analysis. A detailed theoretical background on stability analysis is given separately (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 μ_h is the temporal mean and σ_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 σ_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

$$275 \text{Farm richness}_h | \epsilon_k \sim \text{Poisson}\left(e^{\beta^T x_h + \epsilon_k}\right)$$

$$276 \epsilon_k \sim N(0, \sigma_K^2)$$

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

$$\begin{aligned} 297 \quad \text{logit } \mathbb{P}(\text{Livestock oriented}_h) | \epsilon_k, \epsilon_r &= \beta^T x_h + \epsilon_k + \epsilon_r \\ 298 \quad \epsilon_k &\sim N(0, \sigma_K^2) \\ 299 \quad \epsilon_r &\sim N(0, \sigma_R^2) \end{aligned}$$

300

Equation 3

301

302 **Temporal yield stability**

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

317

$$\begin{aligned} 318 \quad \text{Stability}_h | \alpha_k, \epsilon_h &= \beta^T x_h + \alpha_k + \epsilon_h \\ 319 \quad \alpha_k &\sim N(0, \sigma_K^2) \\ 320 \quad \epsilon_h &\sim N(0, \sigma^2) \end{aligned}$$

321

Equation 4

322

Variable selection first involved developing a list of potential drivers of yield stability. We then manually inspected and eliminated variables with extreme collinearity or extreme imbalance. This was 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 term¹ 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

¹ 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).

richness was explained for the pooled model, with a decrease for the mixed ($R^2 = 0.42$), crop-only ($R^2 = 0.38$), 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 ²	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 ²	-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 ²	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 ²	-1.20 (1.54)		-1.82 (1.00)	*	-1.25 (0.75)	*	0.52 (1.51)	
<i>Random Effects</i>								
σ^2	0.16		0.13		0.26		0.35	
σ_K^2	0.12		0.07		0.08		0.04	
ICC	0.42		0.34		0.24		0.10	
Marginal R ²	0.272		0.132		0.192		0.162	
Conditional R ²	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 3Erreur ! 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>		
σ^2	3.29	
σ_K^2	9.76	
σ_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

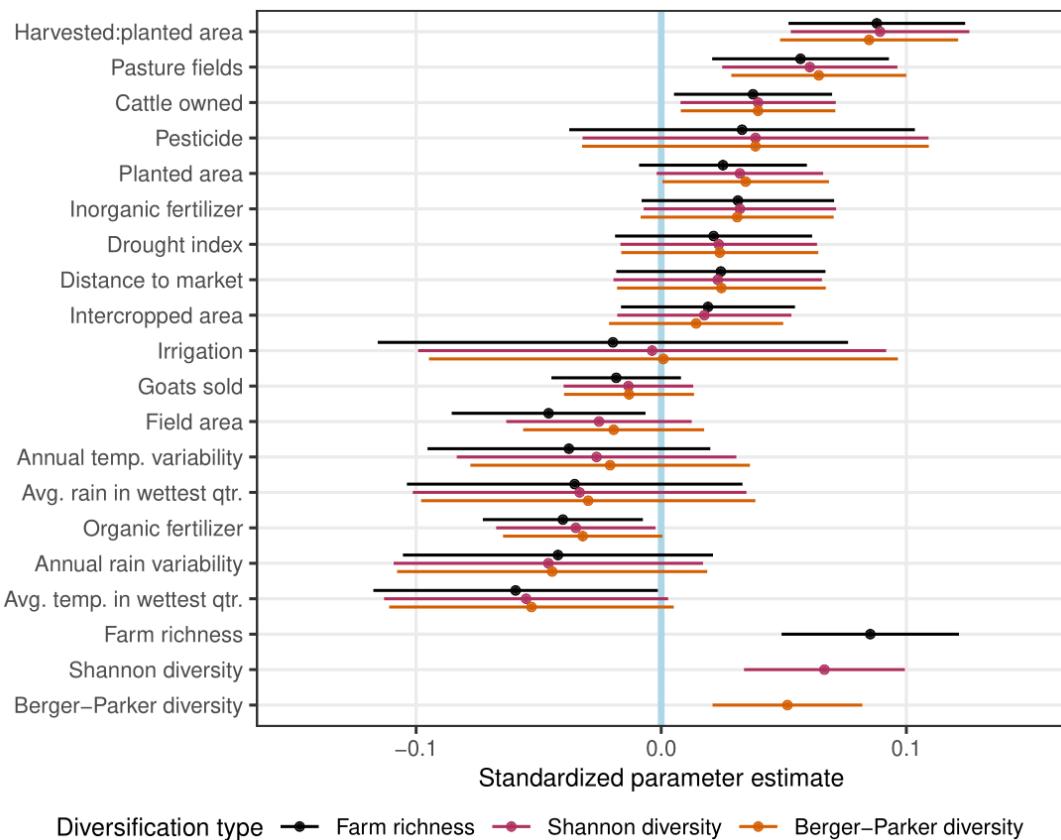
420 Temporal yield stability between 2011 and 2015 in Ethiopia had a median of 1.76. To give an example
 421 of this, a household with a stability of 1.76, or equivalently an inverse CV of $1.76^{-1} = 0.57$, could have
 422 a mean caloric yield in 1 year that was similar to its average over the three 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.

452



453

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

457

458 Parameter estimates for non-diversity predictors were mostly similar across the three models (Fig. 4,
 459 Table A5 in the Appendix). The strongest non-diversity predictor of household yield stability was the
 460 proportion of harvested area to planted area, which was statistically significant and similar in
 461 magnitude to the effect of farm richness. The number of pasture fields was also statistically significant
 462 and positively associated with stability, as was cattle headcount albeit to a lesser extent. The
 463 proportion of area with organic fertilizer was negatively associated with stability, although not at the
 464 0.05 significance level for one of the models. At the 0.1 level, the average temperature in the wettest
 465 quarter was the strongest negative predictor of stability. The region and dominant crop conditioning
 466 variables were significant at the 0.05 level. Intra-class correlation was low, at about 18% for all models,
 467 so stability can be quite different for households within the same kebele (Table A5 in the Appendix).
 468 The explained variance was similar for all models, with a marginal and conditional pseudo- R^2 of 0.157
 469 and 0.315 respectively for the farm richness model. Models using the other stability measures
 470 performed similarly (Supplementary Information S1-6).

471

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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797 **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

798 *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				
		Mean	SD	Min.	Median	Max.
<i>Continuous predictors</i>						
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	629.343205.820184.000595.8331177.333				
Avg. temp. in wettest qtr.	Average monthly temperature (°C) in the wettest quarter, based on the past 30 years	184.193	28.713106.000183.000	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>		Count				
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>		% True				
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>		Mean	SD	Min.	Median	Max.
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

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

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

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

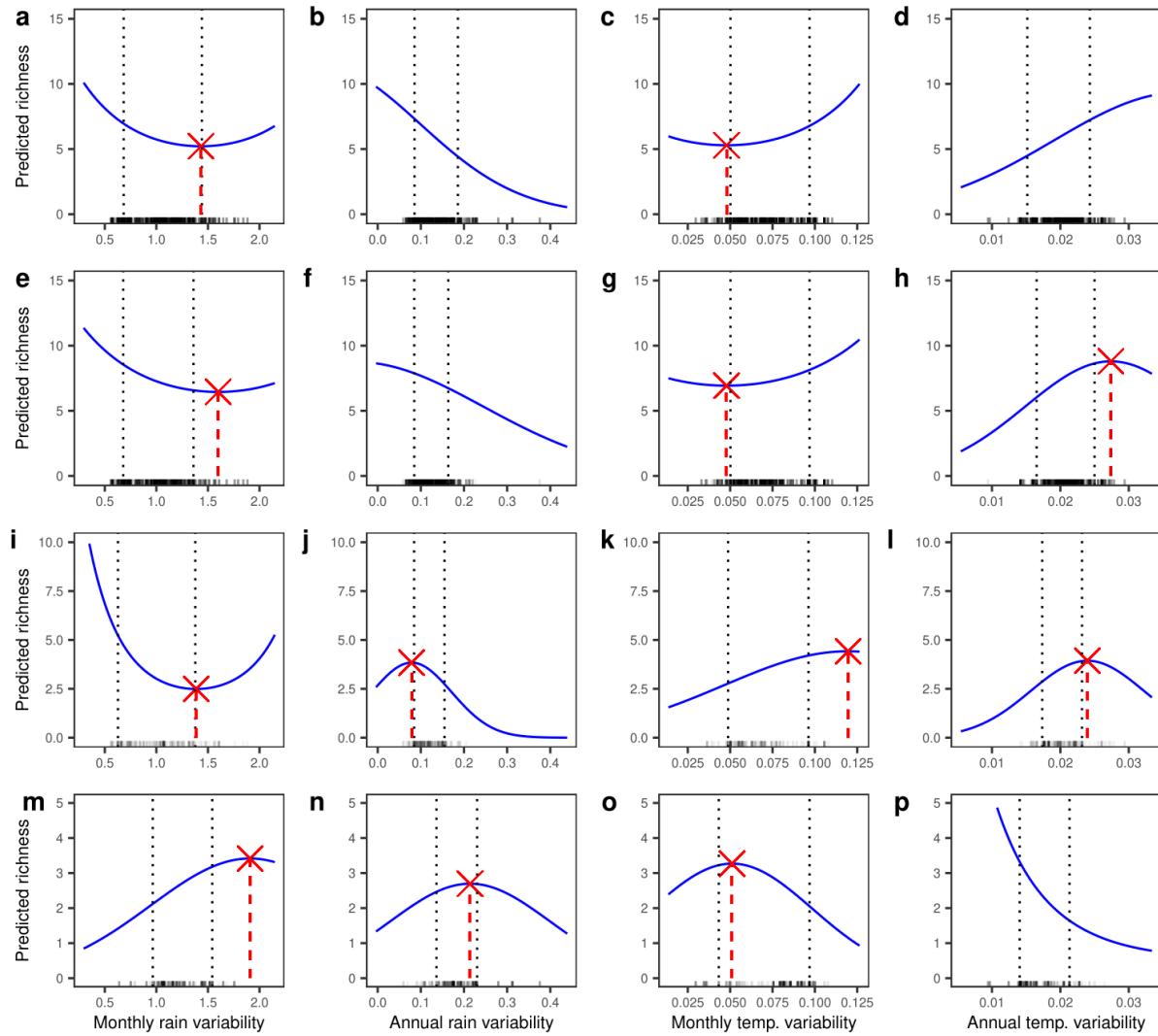
Farm specialization	Field area	Beehive ¹	Month-to-month temp. mean	Topographic wetness index
	Cultivated area		Month-to-month temp. CV	Workability
	Harvested area		Avg. rain in wettest qtr.	Nutrient availability
	Pasture area		Avg. temp. in wettest qtr.	Nutrient retention
	Damaged area		Drought index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

Note: ¹owned, ²milked, ³sold, ⁴slaughtered, ⁵milk yield

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

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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>						
σ^2	0.16		0.16		0.16	
σ_K^2	0.04		0.04		0.04	
ICC	0.19		0.18		0.18	
Marginal R ²	0.157		0.153		0.149	
Conditional R ²	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.*