Avances de Investigación

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Using a co-occurrence index to capture crop tolerance to climate variability: a case study of Peruvian farmers

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GRADE
Grupo de Análisis para el Desarrollo

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ABSTRACT

Peruvian small farmers in the Andes mountain region have historically faced wide climate variability (from year to year and within the crop growing season). Traditional knowledge and practices, including crop portfolio diversification and selection of tolerant crops, aim at safeguarding food security even in "bad" years, when climate- or market-related risks materialize. In spite of this historical knowledge and experience, accelerated climate changes pose new challenges that farmers struggle to adjust to, especially due to a lack of timely information and financial and physical resources. Understanding how farmers are autonomously adapting is a pending need, to be able to inform policy makers about the bottlenecks and sustainable practices that can be strengthened to support efficient adaptation. This study focuses on one type of adaptation: selecting crops that seem to be more tolerant to variable climate conditions. We use Fridley et al.'s co-occurrence index (2007), which measures a species' ecological niche breadth, to estimate the relative tolerance of crops to a range of environmental conditions. Using census data (district panels from 1994 and 2012), we estimate crop tolerance for 252 crops cultivated in diverse environmental conditions throughout the country, ranging from the Andean Highlands to Coastal and Amazon Rainforest regions. We test the suitability of the crop index for capturing crop tolerance to variable climate conditions (maximum, minimum, and average temperatures, and precipitation) using two definitions of climate variability. We find

the expected positive correlation between the index and climate variability, which confirms the index's suitability for capturing relative tolerance to climate variability. We also apply the index empirically to explore the role of intraseasonal climate variability (during the growing season) on the relative tolerance of farmers' crop portfolio. Although further analysis is needed to fully model farmers' decisions, our preliminary estimates show that farmers adjust their portfolios to include more tolerant crops when facing increased climate variability.

INTRODUCTION

Climate change can have profound impacts on rural economies, due to the high sensitivity of agriculture to climate-related conditions and uncertainties. Increasing temperature, increasing carbon dioxide, higher frequency of extreme events (drought, flood, hail, heat waves, among others), and less predictable rainy seasons have been documented as some of the main climate changes observed and forecasted for the near future (Porter et al. 2014, Dasgupta et al. 2014, Easterling et al. 2007). All of these pose challenges to agricultural systems as far as coping with negative effects and taking advantage of potential opportunities, especially in places like Peru, where farmers lack the physical and financial assets needed to access technology and information for effectively adapting to changing conditions (Dasgupta et al. 2014, Easterling et al. 2007, Lin 2011, Reardon et al. 2007). In spite of these limitations, however, traditional knowledge and experience facing extreme climate events—including crop diversification and selection of tolerant crops—stand out as Andean farmers' key assets for adapting to these new challenges. Understanding how farmers are autonomously adapting is a pending need, to be able to inform policy makers about the bottlenecks and sustainable practices that can be strengthened to support farmers' efficient adaptation. This study aims to contribute understanding of the role that climate variability plays in farmers' risk-minimizing crop portfolio decisions. In particular, the study estimates the relative degree of crop tolerance to climate variability. After testing the suitability of the estimated crop index for measuring relative tolerance to climate conditions, the index is applied in an investigation of whether farmers respond to an increase in climate variability by substituting in crops that tolerate more diverse climate conditions.

Studies in crop science and plant physiology (Porter & Semenov 2005, Craufurd & Wheeler 2009) as well as in climate economics (Hsiang 2016; Dell, Jones, & Olken 2014), have advanced our understanding about how increasing temperatures and a higher frequency of extreme events may affect major food crops like wheat, maize, and rice. The new climate economics literature has mostly focused on the effects of changes in climate (often using short-term variation) on the yield of major crops, while crop science has advanced our understanding of the effects of short-term climate features (average and variability) on crop growth and stages of development. Diversified crop portfolio decisions, however, have received far less attention in the literature on the impacts of climate change, despite their historical importance in helping mountain farmers cope with climate uncertainty and take advantage of plots' heterogeneous environmental conditions (Porter et al. 2014, Netting 1993). The limited number of studies about the effect of climate change on crop portfolio decisions is partially explained by the lack of data and methodologies available for assessing crop resilience to climate variability. While some studies analyze changes in the degree of concentration of crop portfolios, it is still hard to assess whether those changes are due to market drivers (higher crop price or lower production costs), or due to a higher climate risk that is inducing farmers to concentrate their portfolios towards more tolerant (probably less profitable) crops. Measuring relative crop tolerance to climate variability can contribute to understanding whether changes in the degree of crop portfolio concentration are an adaptation response by farmers to an increase in climate variability.

Crop tolerance is directly linked to the concept of ecological niche breadth (Grinnell 1917, Elton 1927, Hutchinson 1957, Holt 2009), which represents the range of environmental conditions where a species can survive (such as temperature, humidity, and salinity, as well as abundance of prey, predators, or mutualists) (Rodriguez-Cabal et al. 2012, Stachowicz 2012, Afkhami et al. 2014). The classical expectations that stable conditions tend to allow specialized species to subsist while more variable conditions tend to increase the odds of survival of generalist species (MacArthur & Levins 1967) should also hold for crops. To measure crops' niche breadth we estimate Fridley et al.'s co-occurrence index (2007) using information on crops and cultivated area from the 1994 and 2012 Peruvian national agrarian censuses. In contrast with other niche breadth indices, co-occurrence indices assess the niche breadth of a focal species using information on the presence of other species. The Peruvian census panel provides a unique opportunity to measure the impact of climate changes in a megadiverse system with a large number of crops and ecosystems, despite the limited amount of information available about climatic drivers of crop performance. To assess whether the crop index is suitable for analyzing the role of climate variability in crop portfolio decisions, we evaluate the sensitivity of the crop index to climate variability, considering 30-year district average estimates of maximum, minimum, and average temperatures and of precipitation levels. While climate variability can be represented in different ways, for the purposes of this study, we utilize two representations of climate variability: (i) the amount of heterogeneity in average conditions between the crop's different growing locations (the more heterogeneous, the more variable), and (ii) the amount of heterogeneity in local temperature ranges between the crop's different growing locations (the more heterogeneous, the more variable). Our findings show the expected positive correlation of the index with climate variability (the more variable climate conditions are where the crop grows, the more tolerant the crop is). Finally, we use the crop index to estimate the effect of changes in climate variability during the growing season on the relative tolerance of farmers' crop portfolios. To do so, we estimate both the average district niche breadth for the years 1994 and 2012 and the effect of changes in climate conditions on crop portfolio tolerance at the district level, controlling for individual (short-term) time-invariant characteristics.

The article is structured as follows. The next section describes the data and methodology used to estimate the co-occurrence index and to test its suitability for measuring crop tolerance to climate variability. It also explains the method used to apply the crop co-occurrence index in the analysis of the role of climate variability on crop portfolio decisions. Section 3 discusses the results, and Section 4 concludes and raises questions for future research.

1. METHODS

1.1. Data

Crop data

We used crop species data from the Peruvian agrarian censuses gathered by the National Institute of Statistics and Informatics in the years 1994 and 2012 (INEI 2014). Crop production and farmer descriptions were available at the district, province, and department levels[4] for both years. We used data at the district level, the smallest political-administrative unit. Since some district boundaries changed between census years (mostly due to the creation of new districts), when needed we aggregated districts to guarantee spatial comparability across years. Crop species codes were made compatible as well.

Climate data

We used interpolated temperature and precipitation data at ~1 km resolution to characterize climate conditions for each census year—that is, 30-year averages for the periods 1964-1994 and 1982-2012 (Ponce, Arnillas, & Escobal 2015). We focus on the trimester from November

4 Peru is geographically divided into three political-administrative levels, consisting of 25 departments, 196 provinces, and 1,867 districts.

to January, when the rainy season is well established in the Andean region and most annual crops are already sown and growing. This is the trimester when crops are most likely to be affected by climate variability.

Regarding the climate estimates, each dataset (1964-1994 and 1982-2012) was independently interpolated by Ponce, Arnillas, and Escobal (2015) using the protocol proposed by Lavado, Ávalos, and Buytaert (2015). First, they gathered daily temperature and precipitation records at meteorological stations, available online from the National Service of Meteorology and Hydrology (SENAMHI). Then, they computed monthly mean, maximum, and minimum temperatures, as well as average monthly precipitation. They used co-kriging (as in Buytaert et al. 2006) to account for spatial correlation between these three temperature variables and altitude (included as a covariate of each one). To interpolate precipitation, they used the average trimonthly precipitation probability acquired by the Tropical Rainfall Measuring Mission in 2015 as a proxy for the spatial distribution of precipitation. The TRMM data was assumed to be a good estimate of previous years because the spatial distribution of precipitation is strongly constrained by topography and wind direction, and no evidence indicated that either one of these had changed in the last 50 years (Ponce, Arnillas, & Escobal 2015: 218). They averaged the resulting ~1 km minimum, maximum, and mean temperature estimates as well as the precipitation estimates at the district level, excluding pixels at an altitude over 4800 meters above sea level (where no agricultural activity is likely to be biologically viable).

1.2. Fridley's θ_{sim} as a crop tolerance index

Fridley et al.'s co-occurrence index (2007) was used to estimate a crop species' tolerance to diverse environmental conditions. A co-occurrence index takes advantage of the fact that a focal species that tolerates a broad range of environmental conditions should co-occur with a greater number of species across different sites than does a focal species with a narrower niche, as long as sites are appropriately sampled. That is, if the set of species that co-occur with a focal species differs across sites, it is highly likely that the environmental conditions characterizing those sites also differ. In such a case, we can conclude that the focal species occupies a wide ecological niche (i.e., tolerates a broad range of environmental conditions). In contrast, if a focal species co-exists with the same set of species in every site, it is likely that those sites are very similar to one another, and thus the focal species occupies a very narrow niche.

We used the multiple-site Simpson index to measure crop's tolerance, as it is more robust than alternative indices (Manthey & Fridley 2009). Following Baselga, Jiménez-Valverde, and Niccolini (2007: 643), the index for a focal crop is defined as

$$M_{sim}^{k} = \frac{\sum_i (S_i) - S_T}{\left[\sum_{i<j} \min(b_{ij}, b_{ji})\right] + \left[\sum_i (S_i) - S_T\right]}$$

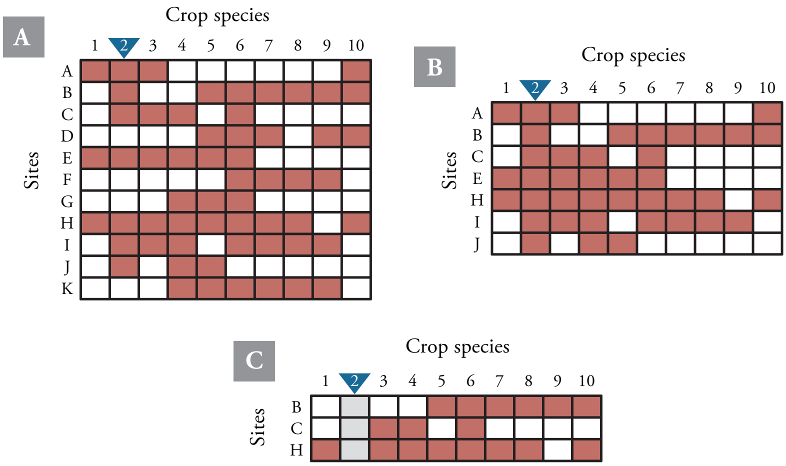
where index i represents a site where the focal crop k grows, S_i represents the number of crop species growing in site i, S_T is the total number of crop species, and b_{ij} represents the number of crop species that grow in site i but do not grow in site j. (In this study, a site is the same as a district.)

In spite of its suitability for measuring species' niche breadth, M_{sim}^{k} may be biased by differences in species abundance. To avoid this potential problem, (i) we excluded crops found in fewer than 20 of the 1,732 sites (districts), and (ii) for each crop, we took 500 random sample, s, of 10 sites each and averaged the $M_{sim,s}^{k}$ indices estimated for them (see Diagram 1 for an example of the estimation procedure using a threshold of 6 sites instead of 20). Following these considerations, the index for each crop species is

$$\theta_{sim}^{k} = 1 - \sum_{s=1}^{500} (M_{sim,s}^{k})$$

In this specification, θ_{sim}^{k} ranges from 0 to 1, with higher values signaling a higher tolerance to diverse environmental conditions (i.e., a wider niche breadth).

Diagram 1
Example of the θ_{sim}^{k} estimation procedure with a minimum threshold of 6 sites (instead of 20)



For each crop species found in more than x=6 sites (Fig A):

a) Select the sites where the species is present (Fig B).
b) Choose x/2=3 sites (districts) randomly (Fig C).
c) Measure similarity between sites (M_{sim}) using the other crop speies only.
d) Repeat steps (b) and (c) n=500 times.
e) Compute the average of the n=500 results obtained in (c), and substract that average from 1.

1.3. Testing the suitability of the index for studying crops' tolerance to changing climate conditions

As previously mentioned, a species with a wider niche breadth can survive in more diverse environmental conditions. Although climate conditions are part of such environmental factors, there is no *ex ante* guarantee that θ^k_{sim} is strongly correlated with the climate conditions of interest here. If there are other factors that are weakly or not at all correlated with the climate conditions of interest but that have more influence on the niche breadth of a crop species, changes in θ^k_{sim} may not successfully capture the crop's relative tolerance to changes in climate conditions.

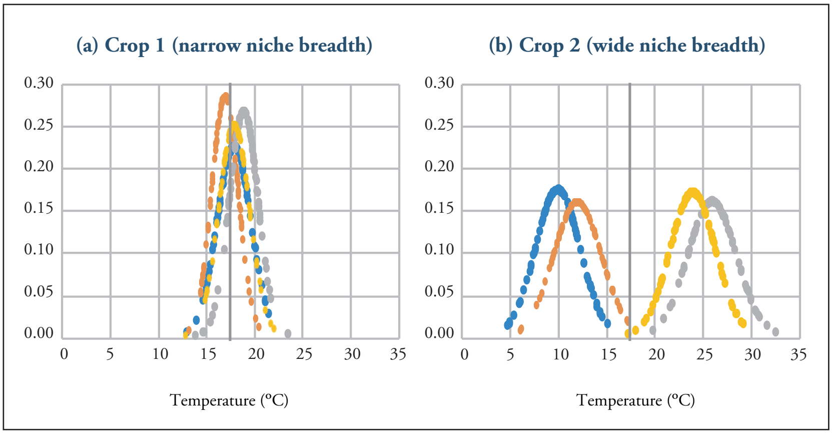
To test whether θ^k_{sim} is a suitable index for such an analysis, we explored its sensitivity to climate variability in two ways:

(i) Extent of the difference in average climate conditions between the districts where a specific crop grows

For this analysis we tested the correlation between θ^k_{sim} and the interquartile range (IQR[5]) of the four climate indicators across districts (minimum, maximum, and average temperatures and precipitation). We explored, for example, how similar minimum temperature is between the districts where each crop grows. The larger the difference in average climate conditions (IQR) between districts, the higher the crop's θ^k_{sim} estimate should be (see a simplified example in Figure 1).

5 The interquartile range is a measure of dispersion or variability, and it has the advantage of being robust in the presence of outliers in climate estimates.

Figure 1
Distribution of daily temperatures in each district where the studied crop grows (these two crops grow at sites with different average local temperatures but the same average global temperature)

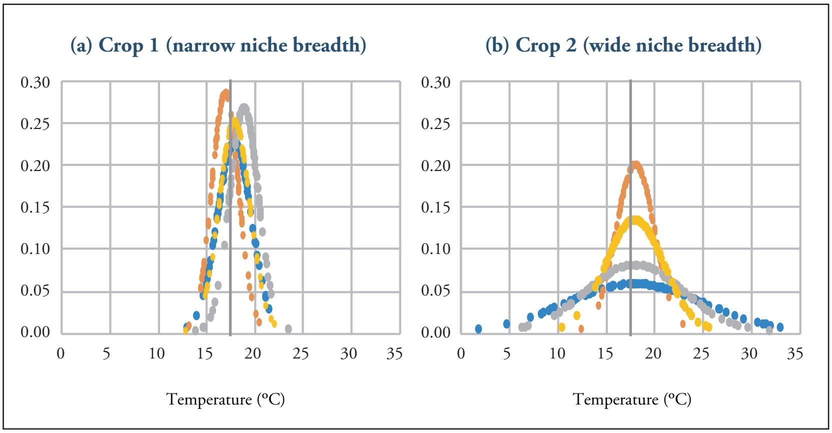


Each curve shows the distribution of daily temperatures during the growing season at a single site where the crop grows. Each crop grows in 4 sites, and both crops grow at the same global average temperature, 18˚C. Given that Crop 2 grows at sites with different average temperatures and Crop 1 grows at sites with very similar conditions, we expect that $\theta_{sim}^{Crop\ 2} > \theta_{sim}^{Crop\ 1}$.

(ii) Extent of the difference in intraseasonal climate variability between the districts where a specific crop grows

For this analysis we tested the correlation between θ_{sim}^{k} and the IQR of the within-district temperature range. A district's intraseasonal temperature range was measured as the difference between the maximum and the minimum temperatures within that district during the growing season (November-January trimester). We expected this correlation to be positive since for similar average temperatures, crops with a broader ecological niche should be able to tolerate a broader temperature range (see Figure 2 for a simplified example). We controlled for average global temperatures when estimating the correlation between θ^k_{sim} and the IQR of within-districts temperature range, as a larger temperature range in warm areas may not be as challenging for crops as it is for them in cooler areas.

Figure 2
Distribution of daily temperatures in districts where a crop grows (these two crops grow at sites with the same average global temperature but different levels of intra-site variability)



Each curve shows the distribution of daily temperatures during the growing season at a single site where the crop grows. Each crop grows in 4 sites, and both crops grow at the same average global temperature, 18˚C. Given that Crop 2 grows at sites with different levels of local temperature variability and Crop 1 grows at sites with very similar conditions, we expect that $\theta_{sim}^{Crop\ 2} > \theta_{sim}^{Crop\ 1}$.

1.4. Application of θ^k_{sim} to study the role of intraseasonal climate variability on Peruvian farmers' crop portfolio decisions

Crop portfolio tolerance to climate variability at the district level

We applied the θ^k_{sim} index to study whether farmers adjust their crop portfolio to better tolerate increasing intraseasonal climate variability. Using the 1994-2012 district census panels, we computed the crop portfolio tolerance index at the district level as follows:

$$\theta^d_{sim} = \sum_{f=1}^{m_d} \left(\underbrace{\sum_{k=1}^{n} (\theta^k_{sim} * A_{kfd}/A_{fd})}_{\text{Farmer's crop portfolio index}} \right) * A_{fd}/A_d$$

where *d, f,* and *k* represent the district, farmer, and crop, respectively. A_{kfd} is the area allocated by farmer *f* to crop *k* in district *d*; A_{fd} is the area cultivated by farmer *f* in district *d*; and A_d is the cultivated area in district *d*. This index was estimated for both census years.

It is important to mention that the crop data used to estimate θ^k_{sim} included individual crops only; that is, companion crops (intercropping practices) were excluded because they were reported as a group in 1994, with no detail on the individual crops involved in each group. As mentioned above, rare crop species (cultivated in fewer than 20 of the 1732 districts) were also excluded from the estimation of θ^k_{sim}. To ensure an adequate representation of average district crop portfolios, the analysis of crop portfolio tolerance focused exclusively on districts with more than 70% of their cultivated land devoted to crops with θ^k_{sim} estimates. Most districts passed this threshold, and were thus included in the analysis (91%, 92%, and 84% of the Highlands, Coastal, and Rainforest regions, respectively).

A preliminary estimation of the effect of changes in climate variability on θ^d_{sim}

We performed a preliminary[6] estimation of the effects of changes in climate variability on θ^d_{sim}, taking into consideration two key issues that may otherwise induce bias. First, we allowed for potentially nonlinear effects of climate variability involving other climate features (Dell, Jones, & Olken 2014). In particular, we included the interaction between temperature range and average temperature. Second, we controlled for conditions that show no major changes in the medium term (e.g., biotic and abiotic environmental conditions variable across the altitudinal gradient, local traditional knowledge about agricultural practices, among others). To reflect the importance of these two issues, we explored three regression models:

1. a base OLS model that included only temperature range and a year dummy for which the estimation used pooled census data (1994, 2012);

6 Farmers' decisions about the types and combination of crops they grow depend on a myriad of factors besides climate conditions, including relative prices of inputs and products, access to traditional and modern technology and information, individual preferences, physical and social capital, relative productivity of labor in alternative non-farm sectors, among others. Also, several studies argue about the importance of crop diversification as a potentially effective adaptation strategy to climate change (Lin 2011; Tuteja, Gill, & Tuteja 2012). The analysis performed in this study is preliminary. A following paper more thoroughly models the role of intraseasonal climate variability in crop portfolio decisions, looking into intercropping, diversification, and selection of tolerant crops.

2. a partial model that added the interaction between temperature range and average temperature to the base model; and
3. a full model that also included district fixed effects to control for invariant features that may affect θ^{d}_{sim}. The final model is robust to correlation between unobserved invariant factors and the climate conditions included in the model (Wooldridge 2012).

District-level observations were weighted by the amount of cultivated land area, to adequately represent Peruvian farmers.

2.1. Testing the suitability of the index for studying crops' tolerance to changing climate conditions

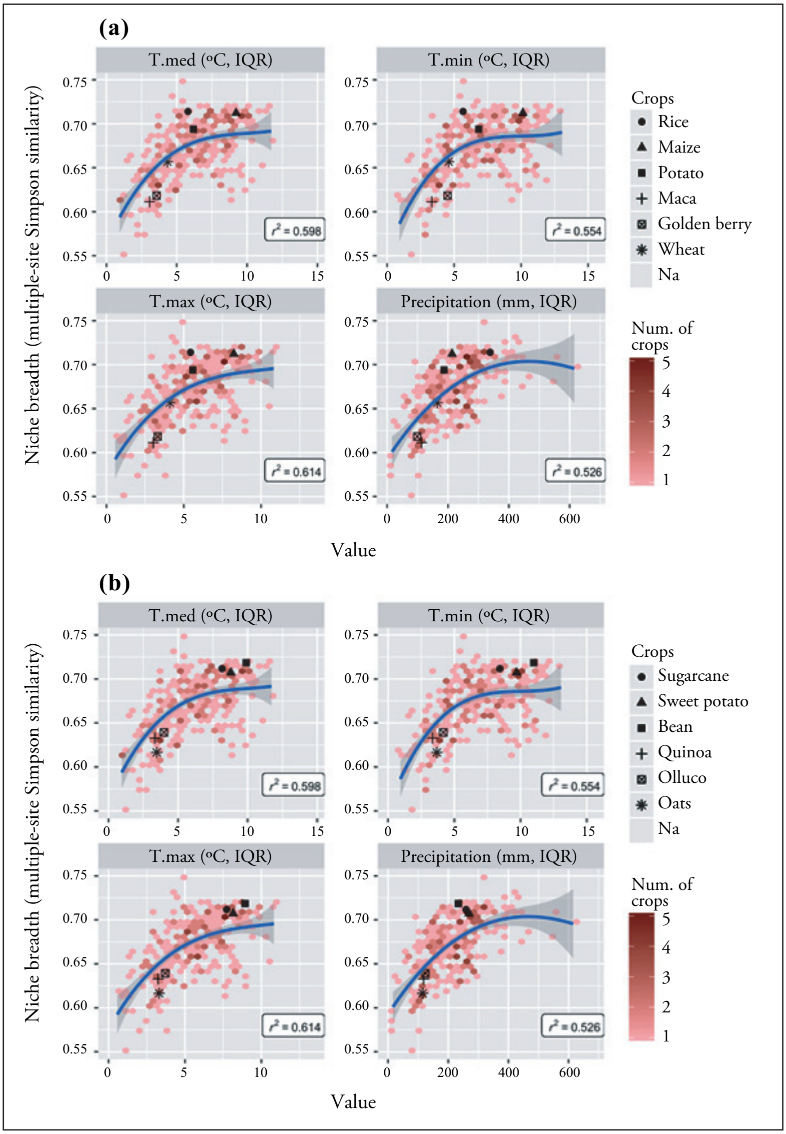
(i) Correlation between θ^k_{sim} and the IQR of the average temperature across the districts where each crop grows

We found a statistically significant positive correlation between θ^k_{sim} and the IQR of the average temperature across districts. The correlation is stronger for crops that grow in districts with colder climate conditions. This result confirms that θ^k_{sim} does capture crops' tolerance to variable climate conditions (Annex 2 shows OLS quadratic regression results).

(ii) Correlation between θ^k_{sim} and the IQR of the intraseasonal temperature range across the districts where each crop grows

We confirmed that θ^k_{sim}, which measures ecological niche breadth, is higher for crops that grow in multiple districts that differ more in terms of temperature variability.

Graph 1
Positive correlation between θ^k_{sim} and the dispersion of a district's average climate conditions



Note. Crop-level observations were weighted by the number of districts where each crop grows

Table 1
Positive decreasing correlation between θ^{k}_{sim} and the IQR of the intraseasonal temperature range

Variables	Coefficient
IQR of temperature range across the districts where the crop grows *(i)*	0.098***
	(0.022)
(i)^2	-0.023***
	(0.006)
Average temperature across all the districts where the crop grows	0.008***
	(0.001)
Constant	0.455***
	(0.029)
Observations	252
R-squared	0.40

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses.
OLS estimates weighted by the number of districts where the crop grows.

2.2. Application of θ^{k}_{sim} to study the role of intraseasonal climate variability in Peruvian farmers' crop portfolio decisions

We confirmed that broader temperature variability across districts leads to a higher tolerance in the crop portfolio. That is, as expected, an increase in intraseasonal temperature range (ceteris paribus) leads farmers to increase the relative importance of more tolerant crops in their crop portfolios. As will be discussed in the next section, several factors may affect farmers' decisions related to crop portfolio tolerance and climate variability; the full model in Table 2 controls for average temperature and district fixed effects. The results show that controlling for other factors besides climate conditions (temperature average and variability) is key to avoiding biased estimates.

Table 2
Estimation of the role of a district's intraseasonal climate variability on θ^d_{sim}

Estimation procedure and covariates	Average marginal effect of Temperature Range	p-value	Number of districts
1. Full model: Fixed effects regression of θ^d_{sim} on TRg, AvgT, and interaction between TRg and AvgT (district fixed effects for 1994 , 2012)	**0.006** ***	**0.000**	**3,378**
2. Partial model: OLS regression of θ^d_{sim} on IQR of TRg, AvgT, their interaction, year dummy, and a constant (pooled regression over 1994 and 2012 data)	-0.001 ***	0.000	3,378
3. Base model: OLS on TRg (pooled regression over 1994 and 2012 data)	-0.007 ***	0.000	1,689

All estimations were weighted by the district's cultivated area.
OLS: Ordinary least squares estimation.
TRg: Temperature Range for November-January trimester (30-year average).
AvgT: Average Temperature for November-January trimester (30-year average).
Detailed results are shown in Annex 3.

The effect of an increase in temperature range on crop portfolio tolerance is positive for districts with an average temperature above 3°C (November-January). Below 3°C, the effect is not statistically significant (Annex 4).

3. CONCLUSIONS AND FINAL REMARKS

The results presented in Section 3 showed that the co-occurrence index discussed in Section 2 is suitable for informing about crop tolerance to climate variability. The co-occurrence index showed a statistically significant positive correlation with both characterizations of climate variability, indicating that crops with wider niche breadth are grown in more diverse climate conditions, and those with narrower niche breadth in less diverse conditions.

Furthermore, we applied the crop index to an analysis of a key feature of crop portfolio decisions—the ability of crops to withstand climate variability during the growing season (another type of climate variability affecting crops). This preliminary analysis showed that an increase in climate variability leads farmers to shift their crop portfolio towards more tolerant crops.

3.1. Suitability of the co-occurrence crop index as a relative measure of tolerance to climate variability

As previously mentioned, households in highland areas like the Andes tend to keep diversified crop portfolios to cope with climate- and market-related risks. Wide temperature ranges during the growing season jeopardize crops' yield and even their survival, especially in high altitude areas. Thus, understanding farmers' response to climate changes through crop portfolio decisions requires assessing the relative tolerance of each crop to climate variability. Additional complementary decisions are involved in adaptive responses to climate change, including adjustment of the degree of crop diversification and selection of specific technologies (such as improving irrigation, companion cropping, introducing resistant varieties, among others), besides other off-farm income-earning strategies (Lin 2011, Dasgupta et al. 2014, Easterling et al. 2007, Ponce 2018). Putting these pieces together would allow for a better understanding of farmers' options and preferences when responding to climate change.

The co-occurrence index is a robust measure of the species niche breadth—that is, the range of environmental conditions that the crop tolerates. The results in Section 3 evaluate the sensitivity of the index to two measures of climate variability: the amount of heterogeneity in average climate conditions between the districts where a specific crop grows, and the amount of heterogeneity in intraseasonal temperature ranges between the districts where the crop grows. The results show a significant positive correlation between both measures of climate variability and the crop index. Emblematic crops of the Andean highlands region such as Maize and Potato, cultivated in most districts of Peru, show a high tolerance to climate variability and larger index values. And although coffee is cultivated in less than a third of districts, it shows a wide niche breadth, as it co-occurs with a large variety of crops in the districts where it grows. Conversely, traditional crops cultivated at high altitudes, such as Quinoa, Maca, and Olluco (cultivated in 862, 428, and 1115 districts, respectively), show narrower niche breadth, with lower temperature and precipitation variability in the districts where they grow—despite their tolerance to very low temperatures and precipitation.

At the same time, while census data allows for the mapping of all agricultural units, it has two key limitations: it lacks information about both plot location and crop variety. As new representative data sources offering these two missing pieces of information become available, it will be possible to estimate crop niche breadth more accurately. Such results will complement thorough studies on resistant varieties developed for specific crops (either by traditional farming or modern laboratories) (Porter et al. 2014, Tapia & Fries 2007). Also, since the specialist-generalist gradient is a relative metric, the crop index estimated in this study is only valid for Peru.

3.2. Empirical application of the crop tolerance index to the study of the role of intraseasonal climate variability (during the growing season) on farmers' crop portfolio decisions

As mentioned above, the ultimate goal of this study is to contribute understanding of the effect of changes in climate variability on farmers' crop portfolio decisions (in areas with little or no public intervention aimed at helping farmers adapt to climate changes). According to our results, the crop co-occurrence index measures the relative tolerance of crops to climate variability and can be aggregated to proxy for crop portfolio tolerance. Nevertheless, Section 2 emphasizes that farmers' crop portfolio decisions are far more complex, and the full model estimated in Section 3 offers a preliminary estimation that includes additional factors. Further study is required to fully model small farmers' crop portfolio decisions, considering that farmers often diversify into other farm activities (husbandry) and off-farm activities (Ponce 2018).

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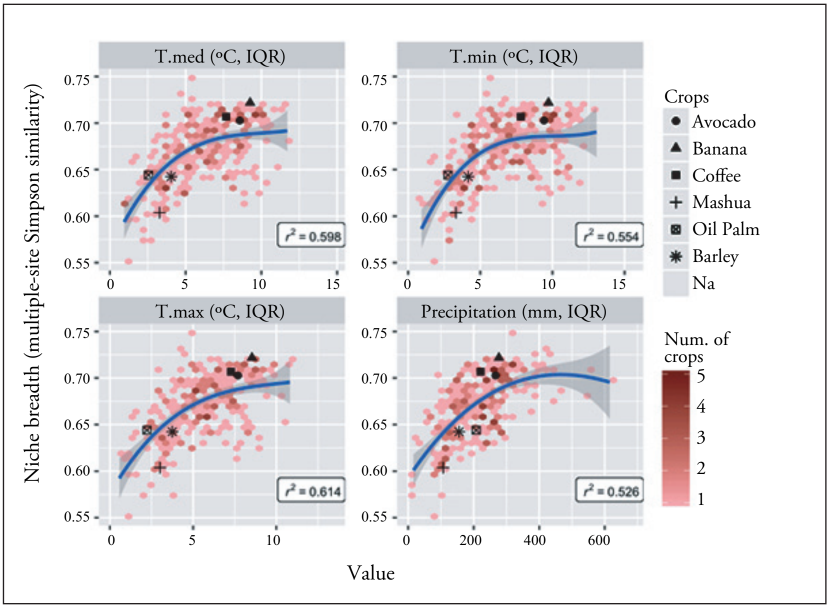
Annex 1

Positive correlation between θ^{k}_{sim} and the dispersion of a district's average climate conditions (additional examples)



Annex 2
Quadratic OLS regression of θ^k_{sim} on IQR of district's average temperature

Variables	**(1)** **Test 1a: IQR only**	**(2)** **Test 1b: IQR and global average temperature**
IQR of local average temperature across	0.030***	0.028***
districts where the crop grows *(i)*	(0.004)	(0.004)
(i)^2	-0.001***	-0.001***
	(0.000)	(0.000)
Average temperature across all districts		0.004***
where the crop grows		(0.000)
Constant	0.547***	0.503***
	(0.013)	(0.011)
Observations	252	252
R-squared	0.597	0.711

Annex 3
Application to farmers' crop portfolio decisions: Effect of changes in intraseasonal temperature range on crop portfolio tolerance θ^{d}_{sim}

Variables	**(1)** **Full model** **(Fixed Effects)**	**(2)** **Partial model** **(OLS)**	**(3)** **Base model** **(OLS)**
District's temperature range during	**-0.007*****	-0.001	-0.007***
the growing season (ii)	**(0.002)**	(0.001)	(0.000)
(i)x(ii)	**0.001*****	-0.000	
	(0.000)	(0.000)	
District's average temperature during	-0.009***	0.002***	
the growing season (i)	(0.002)	(0.001)	
Year dummy	-0.002***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Constant	0.801***	0.676***	0.778***
	(0.042)	(0.011)	(0.004)
R-squared	0.195	0.541	0.269
(within R-sq)			
Observations	3,378	3,378	3,378
Number of districts	1,689	1,689	1,689
N	3378	3378	3378
F(4,1688)	27.89	416.2	259.2
Prob>F	0.000	0.462	0.735
ll	13913	10235	9449

Annex 4
Marginal effects of temperature range evaluated at different levels of average temperature

Average Temperature (˚C)	Marginal effect of Temperature Range on θ^{d}_{sim}	Delta-method Std.Error	z	P>z
8	-0.0012	0.0011	-1.14	0.25
10	0.0002	0.0009	0.17	0.86
12	0.0015	0.0008	1.93	0.05
14	0.0028	0.0008	3.56	0.00
16	0.0042	0.0009	4.51	0.00
18	0.0055	0.0011	4.89	0.00
20	0.0069	0.0014	5.01	0.00
22	0.0082	0.0016	5.03	0.00
24	0.0096	0.0019	5.00	0.00
26	0.0109	0.0022	4.96	0.00

Using a co-occurrence index to capture crop tolerance to climate variability: a case study of Peruvian farmers

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