Biodiversity, Weather Shocks and Rural Incomes in the Tropics[1]

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Abstract

We study the income-supporting role of biodiversity in the context of weather shocks. We use micro panel data covering 20 different tropical countries combined with gridded weather and biodiversity data. We find that weather shocks reduce crop and total income but have ambiguous effects on incomes derived from natural resources. We also find that biodiversity reduces the impact of weather shocks on both sources of income and on total income. In developing countries, biodiversity conservation can therefore reduce the vulnerability of poor rural households to increased weather extremes.

Introduction

A large body of literature in ecology stresses the fundamental role of biodiversity[2] for the productivity and stability of natural systems. Biodiversity supports biomass production and it reduces biomass fluctuations (Hooper et al., 2005; Tilman et al., 2006; Isbell et al., 2015). Biodiversity also supports the production of goods and services that are crucial for welfare

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[2] We use the term biodiversity to describe the total number and relative abundance of species within an ecosystem or a spatial unit (see e.g. Magurran (2013)). In the empirical section we use to term biodiversity to describe the total number of plant species of natural ecosystems within a 1° grid cell (~12,100 km^2). A number of reviews of the economics of biodiversity are available see for instance: Kontoleon et al., 2007; Di Falco, 2012 and Polasky 2002.

(Pearce and Moran, 1994). Despite strong evidence of the importance of biodiversity for ecosystem services in agricultural systems such as pollinator and natural enemy abundances (Chaplin-Kramer et al. 2011), the relationship between biodiversity and income is still largely unexplored. This paper uses a hedonic approach to investigate the impact of biodiversity on rural incomes in the developing world.[3] Understanding the role of biodiversity for ecosystem resilience is particularly important for the rural poor in developing countries, as they face imperfect insurance and credit markets to smooth consumption (Banerjee & Duflo, 2010; Karlan & Morduch, 2010) and are heavily dependent on ecosystem services (Angelsen et al., 2014).

Our analysis is guided by a simple model in which a household allocates labor to different sectors in order to maximize total income. Sectors differ with respect to their vulnerability to weather shocks and to the influence of biodiversity. Sector incomes are thus affected by weather shocks, biodiversity and labor allocation. The model predicts that (1) biodiversity reduces the impact of weather shocks on total income and that (2) its effect on sector incomes is ambiguous. The reason for the latter result is that labor re-allocation, once a shock has materialized, amplifies the production losses in sectors with larger labor productivity declines and dampens the shock in sectors with lower labor productivity impacts. For total income, the effects of factor reallocation cancel out which explains the first theoretical result.

To study the impact of biodiversity on the income of poor rural households in the tropics empirically, we construct a panel of sector-level income data from 8000 rural households in 20 tropical countries (Angelsen et al. 2014), gridded climate data (Harris et al., 2014) and gridded plant species diversity data (Kreft & Jetz, 2007). We use quarterly income and weather data which allows us to estimate the effect of weather on incomes with high temporal resolution. In our empirical specification we estimate the impact of quarterly precipitation and temperature shocks, measured in absolute distances to the mean climate, on sector incomes. We further interact weather shocks with biodiversity levels to measure the impact of biodiversity on income resilience to weather shocks.

Our empirical results show that weather anomalies reduce crop income but partially increase incomes derived from natural ecosystems such as forests and fish stocks (henceforward called

[3] Our approach is similar to the one employed by Barbier (2007) who models biodiversity as an input in a production framework.

environmental income). The effect of weather anomalies on total income is negative but smaller than the effect of weather shocks on crop income. We interpret this result as evidence for a factor reallocation from crop production to environmental production. Further, the results show that biodiversity reduces the effect of weather anomalies on both sector incomes and total incomes.

The magnitude of these effects ranges between zero and 50 % of the incomes but depends however, on whether the shock occurs during the growing cycle of the biological resource or during the harvesting period, as well as on the weather variable. The partially positive impact of weather shocks on environmental income is consistent with a labor reallocation from crop to environmental income and an insurance function of environmental resources as suggested by Baland & Francois (2005).

These results are sensitive to the level of biodiversity. The detrimental impact of weather shocks on crop income, on environmental income and on total income is in fact buffered in areas with more biodiversity. An increase of biodiversity by 1000 species per grid cell or 1.5 standard deviations reduces the effect of weather shocks on incomes by zero to 25 percentage points, but again depends on the timing of the shock in either the growing or the harvesting period, and on the type of weather anomaly. This suggests that increasing biodiversity reduces the direct effect of weather shocks on rural incomes and also the factor reallocation in response to weather shocks from crop to environmental production. This result thus shows the stabilizing role of biodiversity for rural incomes.

This paper relates to two strands of literature at the intersection between environment and development economics. The most obvious is the literature on the value of biodiversity. These include studies on the positive impacts of biodiversity on production (Brock and Xepapadeas, 2003; Tilman et al., 2005; Chavas and Di Falco, 2012) and on risk and resilience (Common and Perrings, 1992; Baumgärtner, 2007; Smale et al., 2007; Quaas and Baumgärtner, 2008; Di Falco and Chavas, 2009; Finger and Buchmann, 2015). However, none of these papers address the question of how biodiversity affects rural incomes while taking factor reallocation across sectors into account. We aim to fill this important gap by making use of a very large set of panel data from twenty different tropical countries.

The second related body of literature is on the estimation of the welfare-supporting role of resources in the developing world. There is, indeed, some empirical evidence highlighting the positive contribution of conservation areas in Costa Rica and Thailand to local incomes (Sims, 2010; Andam et al., 2010; Ferraro et al; 2011). This paper uses a (much) larger panel data set: data consists of 7978 households in 334 villages and 23 countries. It shows that biodiversity conservation can play an important role in poverty alleviation in developing countries. Importantly, it shows that the welfare-supporting role of natural resources is larger in the presence of adverse weather shocks. Although biodiversity conservation may constrain production in rural areas of developing countries, our study shows that it increases the resilience of rural incomes to weather shocks. This insurance effect of natural resources has important welfare consequences for poor rural households that face incomplete credit and insurance markets (Baland & Francois, 2005), and adds to the benefits of protected areas for biodiversity conservation and poverty alleviation (Wunder, 2001; Sunderlin et al., 2005; Andam et al., 2010; Sims, 2010; Ferraro et al., 2015).

The paper proceeds in the following way. In the next section we set up a theoretical framework to highlight the mechanisms and to derive an empirical framework. In the following sections we present our data, derive our identification strategy and show our results. We conclude the article with a discussion.

Model

Consider a rural household that can derive income from agriculture, from natural ecosystems, and from other sources such as wage work or business. The problem of the household is to allocate production factors between these economic sectors in order to maximize utility from consumption. For simplicity we focus on labor and assume that all sector incomes are increasing and weakly concave in labor L^i allocated to the respective sector i. Let $\bar{L}$ denote the total labor endowment of the household such that $\sum_i L^i \leq \bar{L}$. The constraint on labor allocation reflects that households in rural areas of developing countries are mainly self-employed and face malfunctioning labor markets (Banerjee & Duflo, 2007).

Rural incomes are also affected by weather outcomes (e.g. Mendelsohn et al. 2007). Droughts, heavy rains, late frosts or heat waves can harm biological growth and reduce output from agriculture and natural ecosystems. Let ε denote a weather shock, i.e. a deviation from normal weather conditions with negative impact on output such that $\frac{\partial Y^i}{\partial \varepsilon} \leq 0$. This negative impact may vary across sectors with some sectors being more and others being less affected by weather shocks. Labor productivity may also depend on biomass levels such as the standing timber volume or the crop yield. A weather shock that reduces biomass growth therefore also reduces labor productivity such that $\frac{\partial^2 Y^i}{\partial \varepsilon \partial L^i} \leq 0$.

However, biodiversity reduces the impact of weather shocks on biomass production (Isbell et al. 2015). A larger set of species may stabilize biomass production directly via a portfolio or covariance effect (see e.g. Lehman and Tilman, 2000) or indirectly by stabilizing ecosystem services such as pollination or nutrients cycling (MEA, 2005). Let μ denote the biodiversity level. We follow Baumgärtner and Quaas (2010) by assuming that biodiversity has no effect on mean production (i.e. no overyielding in the words of Lehman & Tilman (2000)) but that it reduces the variance of production by reducing the impact of a weather shock, such that $\frac{\partial Y^i}{\partial \mu} = 0$ and $\frac{\partial^2 Y^i}{\partial \epsilon \partial \mu} \geq 0$, respectively. In contrast to Baumgärtner and Quaas (2010) we are concerned with biodiversity of the natural environment and not with agrodiversity that can be manipulated by the farmer. We therefore take the biodiversity level as exogenously given. To focus on the stabilizing effect of biodiversity, we assume that the only effect of biodiversity on labor is through the channel of the weather shock i.e. biodiversity reduces the direct effect of weather shocks on production and the effect of weather shocks on labor productivity.

Taking the weather outcome as given and observing the biodiversity level, the household's optimization problem is,

$$\max_{\boldsymbol{L}} \sum_i Y^i\left(L^i, \mu, \varepsilon\right) \tag{1}$$

s.t. $\sum_i L^i \leq \bar{L}$ and where $\boldsymbol{L}$ denotes the vector of sectoral labor allocation. The first order conditions is

$$\frac{\partial Y^i(L^i,\mu,\epsilon)}{\partial L^i} = \frac{\partial Y^j(L^j,\mu,\epsilon)}{\partial L^j} = \omega \quad \text{for all } i \text{ and } j \text{ and with } \quad i \neq j \tag{2}$$

and ω denoting the shadow value or the marginal productivity of labor. In the case where a labor market with a given wage rate exists, the marginal productivity of labor, ω, equals the wage rate. The optimization behavior of the households implies that the labor allocation is a function of weather shocks and the biodiversity level as they jointly determine the marginal productivity of labor. When a household observes a weather shock it may reallocate labor from more affected economic sectors to less affected sectors. The impact of weather shocks on sector income is therefore given by its direct impact and its impact on labor allocation,

$$\frac{dY^i}{d\varepsilon} = \frac{\partial Y^i}{\partial \varepsilon} + \frac{\partial Y^i}{\partial L^i}\frac{\partial L^i}{\partial \varepsilon} \gtreqless 0. \tag{3}$$

The direct impact of weather shocks on output is negative by assumption but the effect of weather shocks on labor input may be either positive or negative. To see this, note that the optimization implies that the labor constraint holds with equality such that $\sum_i L^i = \bar{L}$. It follows that $\sum_i \frac{\partial L^i}{\partial \varepsilon} = 0$. If labor is withdrawn from one sector it is reallocated to another sector. The overall effect of the weather shock on sector incomes is therefore either negative or positive and depends on the relative size and direction of the direct and the indirect effect. However, the effect of a weather shock on total income is given by

$$\frac{dY}{d\varepsilon} = \sum_i \frac{\partial Y^i}{\partial \varepsilon} \leq 0. \tag{4}$$

Only the direct effects on sector-wise incomes affect total incomes as the labor reallocation effects cancel out. This result follows directly from the envelope theorem.[4]

Next, we consider how biodiversity affects the weather induced income shocks. For the sector-wise income shocks we have

$$\frac{d^2Y^i}{d\varepsilon d\mu} = \frac{\partial^2 Y^i}{\partial \varepsilon \partial \mu} + \frac{\partial Y^i}{\partial L^i}\frac{\partial^2 L^i}{\partial \varepsilon \partial \mu} \gtreqless 0. \tag{5}$$

Biodiversity reduces the direct impact of weather shocks on sector incomes by assumption but has an either positive or negative impact on labor allocation. As before, the labor reallocation impacts cancel out in the income portfolio such that

[4] It is easy to verify this result using $\frac{dY}{d\varepsilon} = \sum_i \frac{\partial Y^i}{\partial \varepsilon} + \sum_i \frac{\partial Y^i}{\partial L^i}\frac{\partial L^i}{\partial \varepsilon} = \sum_i \frac{\partial Y^i}{\partial \varepsilon} + \omega \sum_i \frac{\partial L^i}{\partial \varepsilon}$ with $\sum_i \frac{\partial L^i}{\partial \varepsilon} = 0$.

$$\frac{d^2Y}{d\varepsilon d\mu} = \sum_i \frac{\partial^2 Y^i}{\partial\varepsilon\partial\mu} \geq 0. \tag{6}$$

This result implies that biodiversity reduces the impact of weather shocks on total income.

To illustrate the mechanism in the model, consider a simplified version with only two sectors, agriculture and environment, and linear marginal productivities of labor.

Error! Reference source not found. depicts the marginal productivities over labor allocated to the respective sector. The x-axis shows the labor allocated to agriculture and environmental production. On the right corner, all labor is allocated to agriculture while all labor is allocated to environmental production in the left corner. In optimum, the marginal labor productivity is equal in both sectors which is represented by $L^a = L_0^*$ and $L^e = \bar{L} - L_0^*$ in the figure. Agriculture income is given by the area under the straight line A-E while environmental income is given by the area under the line from E to D. The sum of both areas is total income, i.e. the integral over the curve A-E-D.

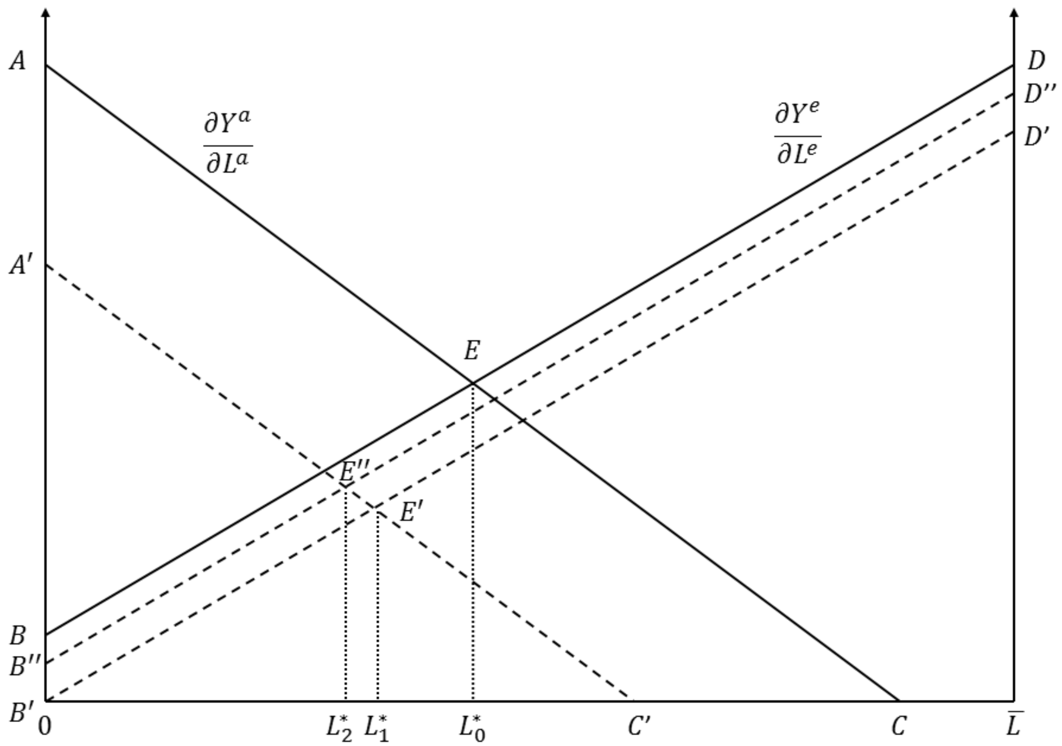

Figure 1: Linear illustration of the model.

Consider a weather shock in a low biodiversity area that reduces the labor productivity in agriculture to the line A'-C' and the labor productivity in environmental production to D'-B'. Without labor re-allocation, the marginal productivity of labor in environmental production is higher than in agricultural production. The new optimal labor allocation changes therefore to L_1^* i.e. labor is reallocated from agriculture to environmental production. Total income reduces to the area under the curve A'-E'-D' but environmental income may increase after the weather shock as a consequence of the labor reallocation. Now consider an area with high biodiversity levels. The same weather shock may decrease the marginal labor productivity in agricultural to the same level as in the previous case (A'-C') but it affects environmental income to a lesser extent. Assume that marginal labor productivity in environmental production decreased only to D''-B''. More labor is allocated to environmental income and the new labor optimum is represented by L_2^*. Although total income decreased less in high biodiversity case compared to the low biodiversity case, agricultural income decreases more as more labor is reallocated to environmental production.

Our theoretical findings suggest that 1) weather shocks reduce total incomes and that 2) biodiversity reduces this negative impact of weather shocks on total incomes. If these two results are also true for sector incomes is an empirical question. Weather shocks would have a positive effect on sector incomes if a positive effect of weather shocks on factor allocation outweighs the direct negative effect of weather shocks on production. Biodiversity would have a stabilizing effect on sector incomes if it counteracted the effect of the weather shock, at least partially. We answer this question empirically in the next sections.

Data

The empirical analysis is based on a large panel of quarterly income data in 20 tropical countries combined with gridded weather and biodiversity data. We describe the data sources for income, biodiversity and weather in the following. The summary statistics are given in Appendix A1 and the distribution of weather shocks are shown in Appendix A2.

Income

The study uses the income data from the Poverty and Environmental Network (PEN) from CIFOR. The PEN survey is the largest survey on rural households that payed special attention to environmental incomes. The data consists of 7978 households in 334 villages and 23 countries with interviews taking place every three month within one year. The survey period was from 2005 to 2010. The selection of the villages was not randomly but the sample is representative for tropical and sub-tropical landscapes with at least some access to forest resources. The survey is described in more detail in Angelsen et al. (2014). The location of PEN study sites are shown in Figure 2.

We use quarterly net incomes measure in PPP dollars per adult equivalent. Incomes are net production costs but capital depreciation is not accounted for. To define the income sectors for our analysis we split the income data into crop income, environmental income and other income. We separate crop income from livestock income as livestock may serve as a buffer stock, following an opposite trend as crop income (see Noack et al. 2015). The median crop income share in our sample is 25 % (see Appendix A1). Environmental income includes all incomes from non-cultivated sources such as fish, timber and non-timber forest products (excluding products from plantations) and other environmental goods and services. The median environmental income share in our sample is 21 %. Other incomes include business, wages and livestock income as well as remittances and government transfers. Although intuition suggests that business incomes and wages may be less affected by weather shocks than agriculture, many wage work is related to agriculture. Local businesses in turn may directly depend on agricultural incomes of their customers to generate income. We focus therefore on crop and environmental incomes and report the estimates for `other incomes' only for completeness.

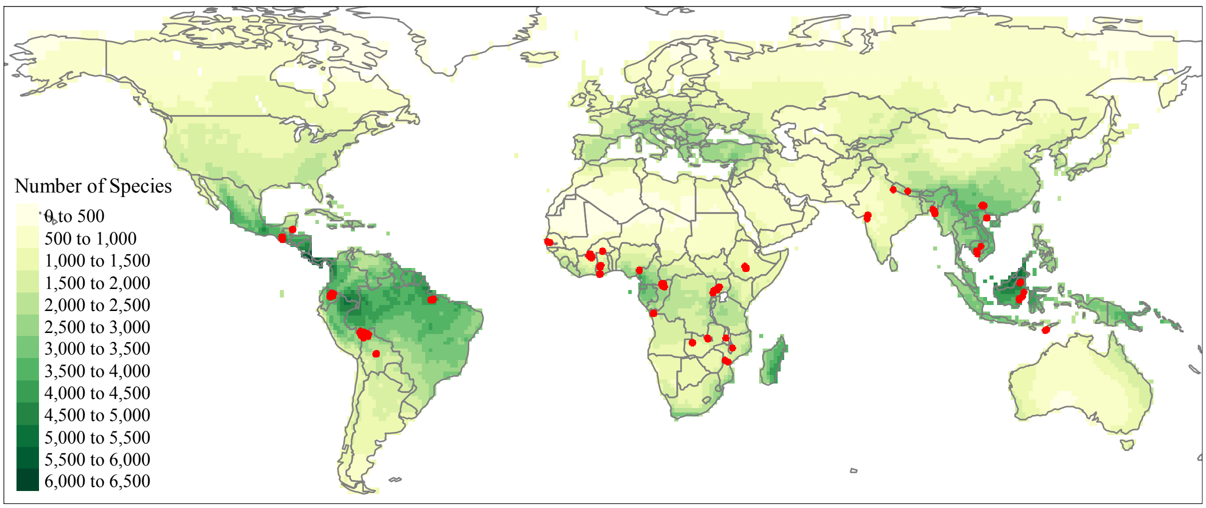

Figure 2 Biodiversity levels from Kreft and Jetz (2007) and PEN study sites. Each PEN study sites represents several surveyed villages.

Biodiversity

The data on biodiversity are gridded data of the number of plant species per 1 degree grid cell from Kreft & Jetz (2007). Kreft & Jetz use 1,032 species richness accounts to compute the gridded data with three different methods. They use kriging which depends on spatial autocorrelation, a regression model that is based on geography, climate, vegetation and evolutionary history as well as a model that uses the information of kriging and the regression model. We use the regression results as they conserve local differences better than the two other models that are based on spatial autocorrelation. Although we use data on plant species richness they may be representative for biodiversity in general as diversity of different taxa is positively correlated (Siemann et al. 1998; Haddad et al., 2001; Qian et al. 2008). We use linear interpolation to compute the village level biodiversity levels from the gridded plant species richness data.

Weather

To relate the household data to climatic conditions we use the gridded climate data of the Climate Research Unit of the University of East Anglia (CRU TS3.21). The CRU data contain monthly time series of temperature, precipitation and other climate variables spanning the period from 1901 to 2012 and covering the whole globe with 0.5 degree resolution. It is based on the analysis of over 4000 individual weather station records (Harris et al. 2014). These data are most commonly used in economic studies (Aufhammer et al., 2013; Dell et al. 2014). To compute the weather shocks per village and quarter we use absolute values of normalized weather deviations i.e. the distance to the normal climate measured in standard deviations. The normalization is based on the village mean and standard deviation of a reference period from 1980 to 2010.[5] This specification assumes first that the expected climate maximizes local production such that any deviation from the mean reduces output and second that local production can adapt to variable climate which we account for with the standardization. This definition of a shock has the advantage that the study villages have similar probabilities to experiences a shock. Geographical selection bias is therefore a minor concern for our results.

We use average temperature and total precipitation of the survey quarter to compute the weather shocks. Alternative specifications such as days in different temperature bins (see e.g. Burgess et al. 2014) are less meaningful for our purpose as our study area spans large parts of the tropics and farmers in our sample cultivate over 300 crop types. While our specification assumes that local deviations from the reference climate are the relevant variables, temperature bins assume an equal response of incomes to an additional degree day irrespective of the local mean.

Empirical Strategy

Our empirical strategy on the effect of weather anomalies and biodiversity on income relies on (i) the panel nature of our dataset and (ii) the exogenous variation in the weather anomalies. Of

[5] Log deviations of weather as in Bazzi (2015) lead to qualitatively similar results but we see no theoretical foundation for declining marginal effect of weather shocks on income in our case.

particular interest is the interaction between the weather shocks and biodiversity.[6] The equation to be estimated is:

$$\text{income}_{\text{ijkt}} = \alpha_1 \,\text{shock}_{jkt} + \alpha_2 \,\text{shock}_{jkt} \times \text{diversity}_{jk} + \beta \,\text{X}_{jkt} + \gamma_{ijk} + \delta_t + \epsilon_{ijkt} \quad (8)$$

Where the dependent variable is income of household i in village j, in World Bank region k and in quarter t. Income is transformed using the inverse hyperbolic sine transformation (Burbidge et al.,1988) to account for the log normal distribution of incomes and the negative values in seasons that are dominated by investment. The interpretation of the coefficients is similar to the interpretation for log-transformed incomes. In the baseline specification, the vector X_{jkt} contains quarterly village level temperature and precipitation means to account for the seasonality of the data. The term γ_{ijk} denotes household fixed effects, δ_t is a linear time trend and ϵ_{ijkt} represents the error term.

The shock variable denotes a vector that includes the normalized precipitation and the temperature anomalies in absolute terms as defined in Section 0. We include anomalies both of the current and lagged quarters as most of the crops or forest products that are harvested in the current quarter were growing already in the previous quarter. We expect therefore that lagged weather shocks which affected plant growth and mortality rates reduces the harvestable biomass while weather shocks in the current quarter may affect either the biomass or the harvesting process.

As we cannot separate the channels of the weather shocks on income, the direct effect and the effect on factor reallocation are both captured by the coefficient α_1. The same holds true for the direct and the factor reallocation effects of biodiversity on income shocks that are both captured by the coefficient α_2. If biodiversity reduces the impact of weather shocks on sector income and total income then $\alpha_1\alpha_2 < 0$, i.e. both coefficients have opposite signs.

The biodiversity measure is

[6] It is important to stress that the interaction between weather anomalies and biodiversity should provide a consistent parameter estimate even if biodiversity is endogenous. Nizalova & Murtazashvili (2016) show both analytically and with simulations that Ordinary Least Squares (OLS) estimate on the interaction effect is biased but consistent. Several authors also exploit the exogenous variation in one variable to estimate interaction effects with one potentially endogenous variable (e.g. Glewwe et al. 2009, Banerjee et al. 2007, 2010).

$$\text{diversity}_{jk} = \mu_{jk} - \bar{\mu}_k,$$

where μ_{jk} is the biodiversity of village j in region k and $\bar{\mu}_k$ is the mean biodiversity in region k. Demeaning by region removes the effect of unobservables that are correlated with biodiversity and vary on regional level (see e.g. Wooldridge (2002, p.330) and Balli & Sørensen (2013)).[7] It also simplifies the interpretation of the coefficients. After demeaning, α_1, measures the marginal effect of weather shocks on income for average region specific biodiversity levels instead of the marginal effect of weather shocks under the absence of biodiversity which would be the case without demeaning.

Biodiversity may be correlated with other variables that change the impact of weather shocks on income. The household fixed affects capture the effect of these unobservables on income levels and demeaning of biodiversity with regional means removes the effect of regional varying unobservables on the interaction term. However, biodiversity may be correlated with some variables even within a region that affect the impact of weather shocks on income. The most relevant variable is terrain which is highly correlated with biodiversity (Kreft & Jetz, 2007) and may affect the access to markets. To control for these confounding factors we include interaction terms of weather shocks with distance to the nearest road and distance to the nearest city in a second regression specification. Furthermore, the impact of weather shocks on income may differ substantially depending on the season. As our study area covers the tropics, seasonality is less pronounced and most areas have several cropping seasons with a growing season exceeding 200 days (Fischer et al., 2012). As it may not be sufficient to include average seasonal climate, we add an interaction term between weather shocks and the average seasonal climate in the second regression specification. We center all controls with the regional means to simplify interpretation of the coefficients.

[7] The effect is the same as interacting regional dummies with the weather shocks. However, the interpretation of the effects changes since α_1 is then the effect of weather shocks on income in the baseline region in the absence of biodiversity. We prefer demeaning because of the ease of interpretation.

Results

This section reports our empirical results. Based on our theoretical analysis we expect that weather shocks reduce total income. We expect further that weather shocks reduce incomes in weather sensitive sectors and that they either increase or decrease incomes of less weather sensitive sectors. We interpret an increase of incomes in sectors in response to weather shocks as evidence for factor reallocation and an income stabilizing function of these sectors against weather shocks. Biodiversity reduces the impact of weather shocks on total income if the interaction term coefficients are positive. The same would be true for sector incomes if factor reallocation is not taken into consideration. If biodiversity also affects factor productivity, a stabilizing effect of biodiversity implies that the coefficients of the interaction of weather shocks and biodiversity have opposite signs to the coefficients of weather shocks.

Table 1 reports regression results of the baseline specification in the first four columns while the results for the specification with additional interacted controls are given in the last four columns. All regressions include household fixed effects, linear time trends and current and lagged quarterly climate means (not shown). The dependent variable is inverse hyperbolic sine transformed crop income, environmental income, other income and total income. The weather shock is represented by the precipitation shock in the current quarter, in the lagged quarter and the equivalent for temperature shocks. In the baseline specification, only biodiversity is interacted with weather shocks. In the second specification with interacted controls, weather shocks are further interacted with mean seasonal precipitation and temperature levels and with the distance to the nearest road and distance to the nearest city. Standard errors are heteroscedasticity robust (round brackets) and clustered at the village level [square brackets]. A specification without biodiversity is given in the Appendix 2 and a specification without lagged weather shocks in Appendix 3.

Table 1: Weather shocks and income

	Baseline specification				Specification with interacted controls			
	crop	environment	other	total	crop	environment	other	total
Precipitation	-0.285	-0.068	0.038	-0.107	-0.175	-0.073	-0.010	-0.062
shock	(0.037)***	(0.021)***	(0.024)	(0.026)***	(0.041)***	(0.023)***	(0.027)	(0.029)**
	[0.181]	[0.056]	[0.043]	[0.083]	[0.208]	[0.059]	[0.052]	[0.097]

Precipitation shock lagged	-0.308 (0.040)*** [0.161]*	0.046 (0.022)** [0.055]	0.072 (0.026)*** [0.057]	-0.068 (0.028)** [0.069]	-0.256 (0.041)*** [0.151]*	0.047 (0.023)** [0.060]	0.068 (0.027)** [0.058]	-0.034 (0.028) [0.066]
Temperature shock	0.004 (0.040) [0.216]	0.135 (0.022)*** [0.085]	-0.014 (0.026) [0.050]	0.142 (0.028)*** [0.092]	-0.190 (0.046)*** [0.198]	0.109 (0.025)*** [0.082]	0.069 (0.030)** [0.055]	0.144 (0.032)*** [0.087]*
Temperature shock lagged	-0.501 (0.040)*** [0.173]***	-0.036 (0.022) [0.057]	0.057 (0.026)** [0.048]	-0.135 (0.028)*** [0.076]*	-0.662 (0.043)*** [0.182]***	-0.027 (0.024) [0.061]	0.068 (0.028)** [0.050]	-0.159 (0.030)*** [0.082]*
Precipitation shock × diversity	0.124 (0.021)*** [0.079]	0.002 (0.011) [0.025]	-0.010 (0.013) [0.021]	0.055 (0.014)*** [0.036]	0.339 (0.036)*** [0.134]**	0.015 (0.020) [0.049]	0.000 (0.024) [0.039]	0.191 (0.025)*** [0.077]**
Precipitation shock lagged × diversity	0.069 (0.026)*** [0.089]	-0.014 (0.015) [0.047]	-0.027 (0.017) [0.049]	0.034 (0.018)* [0.048]	0.438 (0.045)*** [0.163]***	-0.068 (0.025)*** [0.065]	-0.129 (0.029)*** [0.062]**	0.127 (0.031)*** [0.071]*
Temperature shock × diversity	-0.103 (0.031)*** [0.135]	-0.072 (0.017)*** [0.052]	0.055 (0.020)*** [0.037]	-0.083 (0.021)*** [0.065]	-0.470 (0.050)*** [0.217]**	-0.070 (0.028)** [0.077]	0.123 (0.033)*** [0.066]*	-0.113 (0.035)*** [0.106]
Temperature shock lagged × diversity	0.239 (0.027)*** [0.088]***	-0.096 (0.015)*** [0.038]**	-0.003 (0.018) [0.030]	0.041 (0.019)** [0.047]	0.046 (0.040) [0.121]	0.100 (0.022)*** [0.062]	0.034 (0.027) [0.046]	0.082 (0.028)*** [0.068]
Seasonal climate	✓	✓	✓	✓	✓	✓	✓	✓
Household fe	✓	✓	✓	✓	✓	✓	✓	✓
Weather shock					✓	✓	✓	✓

× infrastructure								
Weather shock × climate					✓	✓	✓	✓
Observations	31,134	31,134	31,134	31,134	31,134	31,134	31,134	31,134

The results show overall that 1) weather shocks reduce total and crop income but have mixed effects on environmental and other incomes and 2) biodiversity reduces the effect of weather shocks on total and sector incomes. Generally, the effects go in the same direction in both regression specifications but on average, increase in magnitude when the additional controls are included. The standard errors are sensitive to clustering and most point estimates become statistically insignificant once we control for error correlation within villages. We address this problem below.

Crop income stems mostly from crops that are harvested in the current season but were planted earlier. We therefore use the terms current quarter and harvesting season and the terms lagged quarter and growing season interchangeably. Note also that weather shocks are given in standard deviations (sd) of village weather within the reference period such that the size of one sd in absolute terms differ between villages. We discuss the results of the baseline specification in the following.

Weather shocks generally have a negative impact on crop income. A precipitation shock in the harvesting season reduces crop income by about 29 % per sd while a precipitation shock in the growing season reduces crop income by 31 % per sd. We also find a negative effect of temperature shocks on crop income. While a temperature shock of one sd in the growing season reduces crop income by 52 % temperature shocks in the harvesting season have no measurable impact on crop incomes. In contrast to crop income, weather shocks have mixed effects on environmental income. A precipitation shock of one sd in the growing season increases environmental income by 5 % while a precipitation shock in the harvesting season reduces environmental income by 7 % per sd. A temperature shock in the growing season has no statistically significant impact on environmental income while it increases environmental income by 14 % when it occurs in the harvesting season. The smaller effect of weather shocks on environmental income compared to crop income suggests that environmental production is less sensitive to weather shocks. The positive impact of the precipitation shock in the growing season and temperature shocks in the harvesting season is an indicator for factor reallocation from crop production to environmental production. The factor reallocation to environmental production after income shocks is in line with the theory of common pool resources as insurance for poor rural households. Overall, it shows that the effect of weather shocks on sector income can go in both directions.

For total income, we have the following results. A precipitation shock in the current quarter reduces total income by 11 % per sd and in the lagged quarter by 7 %. A temperature shocks in the previous quarter reduce total income by 14 % per sd. A temperature shock of one sd in the current quarter increases total income by almost 14 %. This result is surprising. A possible explanation is that households sell their natural capital such as timber which increases their income temporarily but may reduce income in the long run (see e.g. Jayachandran, S. (2013)).

However, clustering the standard errors on village level renders many of the parameter estimates statistically insignificant. One reason for the imprecise estimates is the high correlation of the different weather shocks. To address this problem we test for the joint significance of the weather shocks using a Wald test with the baseline regression specification and stander errors clustered at the village level. We find that weather anomalies are jointly significant for crop income and total income at the 5 percent level and for environmental income at the 10 percent level. We therefore conclude that weather shocks have a statistically significant impact on crop, environmental and total income even after correcting for the correlation of the error terms.

The interaction between biodiversity and weather Shocks

Next, we interpret the effect of biodiversity on weather induced income shocks. Biodiversity is measured in 1000 plant species per 1° grid cell. As a reference, on standard deviation in our sample equals 671 plant species. Biodiversity reduces the effect of weather shocks on total, crop and environmental income as most of the coefficients for the interacted terms have opposite signs to the non-interacted weather shocks. This stabilizing impact on total income is driven by the stabilizing impact of biodiversity on crop and environmental production. An increase of 1000 plant species per grid cell compared to the regional average reduces the negative impact of weather shocks on crop income by 7 to 24 percentage points. Only the negative effect of temperature shocks in the current season on crop income increases with higher biodiversity levels. An increase in biodiversity levels also reduces the impact of temperature shocks in the harvesting season on environmental income by 7 percentage points but increases the impact of temperature shocks in the growing season by 10 percentage points. The latter may be an indirect effect of factor reallocation to agriculture but as the effect flips sign after including the controls this interpretation may be treated with caution. Biodiversity reduces the effect of weather shocks on total income by 3 to 8 percentage points which shows that the stabilizing effect of biodiversity on crop income carries over to total income.

Using a Wald test with the parameter estimates from the regression baseline specification and standard errors clustered at the village level we can show that biodiversity has a jointly significant effect on weather induced income shocks for crop income at the 5 percent level and for environmental and total income at the 10 percent level.

To test weather biodiversity stabilizes income, we test $\alpha_1\alpha_2 < 0$ directly using bootstrapping with 1000 bootstrap replications. For each replication we evaluate whether $\alpha_1\alpha_2 < 0$. The fraction of replications for which the inequality holds can be interpreted as the probability that biodiversity reduces the impact of weather shocks on income. Alternatively we integrate the expression $\alpha_1\alpha_2$ over the multivariate normal distribution specified by the point estimates and the covariance matrix and accounting for the correlation of errors at the village level.[8]

Table 2 shows the probabilities of the coefficients for the non-interacted and the interacted weather shocks to be of the *same* sign using the bootstrap and the integration method (in brackets) with the parameter estimates of the baseline specification. We perform the test for each weather shock and its interaction term separately.

Table 2 Biodiversity and Weather Shocks

Prob($\alpha_1\alpha_2 > 0$)	crop	environment	other	total
Precipitation anomaly	0	0.011	0.059	0
	(0.004)	(0.153)	(0.068)	(0.034)
Precipitation anomaly lagged	0	0	0.013	0.002
	(0.056)	(0.009)	(0.081)	(0.069)

[8] We thank Simen Gaure for the implementation of the tests in the R package lfe.

Prob($\alpha_1\alpha_2 > 0$)	crop	environment	other	total
Temperature anomaly	0.016	0	0.007	0.009
	(0.105)	(0.032)	(0.050)	(0.073)
Temperature anomaly lagged	0	0.999	0.628	0.007
	(0.121)	(0.218)	(0.227)	(0.084)

Table 2 confirms the observation that biodiversity reduces the impact of weather shocks on sector and total incomes as the probability of the coefficients for the linear and the interacted weather shock to have the same sign is close to zero in most cases. We conclude the biodiversity reduces the impact of weather shocks on sector and total incomes.

Conclusion & Discussion

In this paper, we examined the effect of biodiversity on weather induced income shocks. Our empirical result confirms in general the theoretical prediction that a weather shock reduces total income and that biodiversity reduces this negative income shock. The empirical results suggest further that labor reallocation occurs and that biodiversity reduces this labor movement. Even though biodiversity could theoretically increase the shock's effect on sector income, the empirical analysis shows that this is not the case.

Biodiversity conservation can therefore increase the resilience of the rural poor to climate change. This is especially true if climate change increase weather variability. Other mechanisms to mitigate the impact of weather shocks on poor rural households such as access to credit and insurance markets, weather robust crop varieties or better access to labor markets can supplement biodiversity conservation. However, biodiversity conservation may be more efficient especially if the off-side benefits of biodiversity conservation are taken into consideration.

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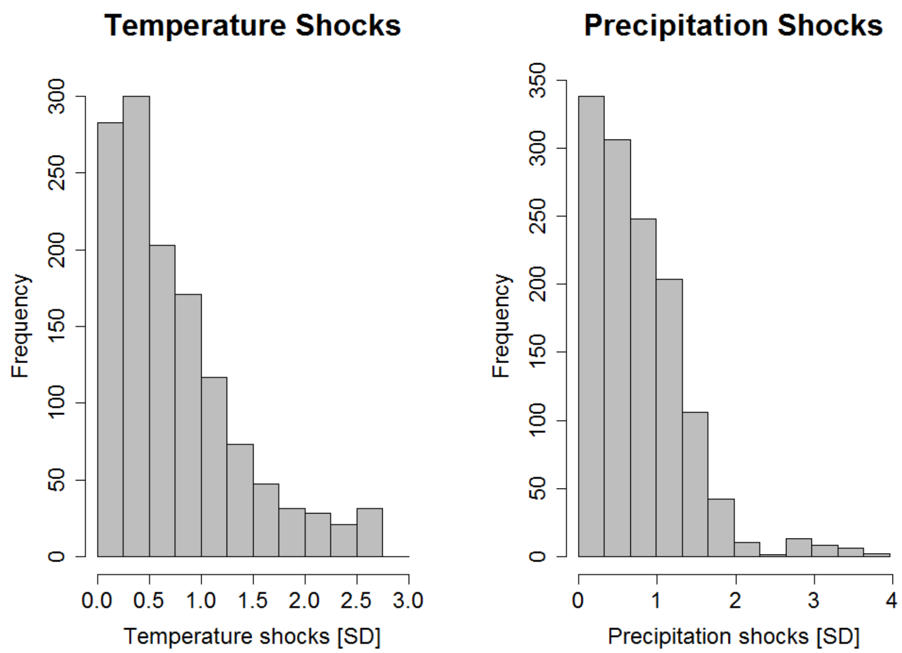
Appendix

Summary Statistics

The following table gives the mean, the standard deviation, and the first, fifth and ninth decile of the key variables of our regressions.

	Mean	**Standard Deviation**	**10th quantile**	**Median**	**90th quantile**
Total income [USD/AEU]	1692	3334	238	857	3523
Crop income [USD/AEU]	434	1367	9	179	879
Crop income share [%]	30	24	1	25	66
Environmental income [USD/AEU]	453	1605	29	142	949
Environmental income share [%]	27	22	4	21	62
Other income [USD/AEU]	805	2275	41	294	1730
Other income share [%]	43	27	9	41	81
Annual temperature [°C]	24	4	17	25	28
Annual precipitation [mm]	1574	653	1008	1236	2686
Diversity [species]	1711	671	997	1662	2612
Road distance [km]	8	23	0	2	20
Distance to nearest city [%]	33	20	6	33	62

1. Weather Anomalies



2. Regression results without Biodiversity

The following table summarizes the results for the regressions as specification (8) and (9) but without biodiversity.

	Baseline				With controls			
	crop	environment	other	total	crop	environment	other	total
Precipitation shock	-0.105	-0.063	0.019	-0.027	0.039	-0.054	-0.025	0.046
	(0.033)***	(0.020)***	(0.022)	(0.023)	(0.054)	(0.026)**	(0.033)	(0.038)
	[0.112]	[0.049]	[0.033]	[0.054]	[0.214]	[0.067]	[0.055]	[0.095]
Precipitation shock	-0.275	0.030	0.048	-0.049	-0.353	0.002	0.071	-0.090
lagged	(0.038)***	(0.021)	(0.026)*	(0.027)*	(0.049)***	(0.022)	(0.031)**	(0.036)**
	[0.112]**	[0.055]	[0.053]	[0.056]	[0.160]**	[0.057]	[0.062]	[0.077]
Temperature shock	-0.015	0.060	0.010	0.091	-0.223	0.087	0.046	0.113
	(0.041)	(0.024)**	(0.027)	(0.032)***	(0.053)***	(0.027)***	(0.034)	(0.039)***
	[0.153]	[0.067]	[0.041]	[0.071]	[0.177]	[0.073]	[0.054]	[0.078]

Temperature shock	-0.314	-0.125	0.063	-0.108	-0.749	0.012	0.102	-0.180
lagged	(0.045)***	(0.022)***	(0.026)**	(0.034)***	(0.058)***	(0.027)	(0.032)***	(0.041)***
	[0.125]**	[0.051]**	[0.040]	[0.061]*	[0.189]***	[0.061]	[0.053]*	[0.081]**
Observations	31,134	31,134	31,134	31,134	31,134	31,134	31,134	31,134

Notes: ***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

3. Regression results without lagged weather shocks

	crop	environment	other	total
Precipitation shock	-0.449	-0.072	0.032	-0.147
	(0.038)***	(0.020)***	(0.024)	(0.025)***
	[0.193]**	[0.051]	[0.040]	[0.081]*
Temperature shock	0.198	0.147	-0.035	0.193
	(0.041)***	(0.022)***	(0.025)	(0.027)***
	[0.223]	[0.088]*	[0.049]	[0.097]**
Precipitation shock	0.220	-0.015	-0.007	0.073
× diversity	(0.021)***	(0.011)	(0.013)	(0.014)***
	[0.077]***	[0.022]	[0.020]	[0.032]**
Temperature shock	-0.020	-0.104	0.062	-0.067
× diversity	(0.031)	(0.017)***	(0.020)***	(0.021)***
	[0.141]	[0.050]**	[0.037]*	[0.066]
Seasonal climate	✓	✓	✓	✓
Hh fe	✓	✓	✓	✓
Observations	31,184	31,184	31,184	31,184

Notes: ***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.