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Sustainable Agriculture in Peru Based on Agrobiodiversity and Climate-Smart Agriculture – Evaluation of a Case Study with Small Farmers in an Andean Basin

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ABSTRACT

The loss of biodiversity and the effects of climate change hurt agricultural production and food security in Peru and around the world. The family farming sector in Peru (97% of agricultural units – AU) faces numerous challenges when it comes to sustainably producing food. To sustain Peruvian agriculture in the face of climate change, climate-smart agricultural (CSA) practices and agrobiodiversity conservation are essential. This document characterizes the level of agrobiodiversity (index IDA) of family AUs in the Crisnejas basin and analyzes the impact of the elements that affect farmers' decisions to apply multiple CSA measures. CSA adoption decisions were analyzed using an econometric analysis framework combining multivariate and ordered probit models for 340 family AUs. Results indicate that AUs with a lower agrobiodiversity index (IDA) have a higher monthly income (IDA = 0.56, 312 USD, Pearson binary correlation, CI = -0.4107). The highest economic income AUs are located between 2,500 and 3,000 meters above sea level (352 USD, CI = -0.3551), have access to irrigation (365 USD, CI = -0.5225), and are also part of consolidated family farms (428 USD, CI = -0.2699). Based on the econometric results, farmers' decisions to adopt CSA practices are influenced by altitude, tenure, age, cultivated area, level of agrobiodiversity, and access to water. A larger number of household members, a better educational level, and a greater distance to the local market increase the probability of intensifying the use of CSA practices in the lower, middle, and upper basins, respectively (significant coefficient estimates, p-value < 0.05). Distance to the farms, cultivated area, and seed storage are other factors associated with the intensity of CSA use (p-value < 0.05). According to the findings, agrobiodiversity must be increased in Peruvian agriculture to achieve a functional and balanced system from an economic, ecological, and sociocultural perspective, as well as carefully developing adaptation/mitigation strategies to address the impacts of climate change on Peruvian agriculture.

Keywords: Crisnejas basin, agrobiodiversity, climate-smart agriculture, family farming, climate change.

INTRODUCTION

Natural resources are being degraded due to a variety of factors, primarily soil erosion and a loss of biodiversity (Adams et al., 2004; Warren et al., 2013). Biodiversity includes elements used for food and agriculture (agrobiodiversity), as well as ecosystem components (Frison et al., 2011). The number of crop varieties that have disappeared from fields over the last 100 years has risen to more than 90% (CIP-UPWARD, 2003) and more than 690 livestock breeds have been lost to extinction (FAO, 2007). In the world's diet, 15 types of crops and eight domestic animals make up 90% of the caloric requirements (Imran et al., 2018). Agrobiodiversity, which is a vital part of agricultural systems and natural habitats, is disappearing at an unprecedented rate.

Agriculture contributes to greenhouse gas emissions as global food demand grows (Lipper et al., 2018). One-quarter of the human-caused emissions of greenhouse gases are caused by agriculture, forestry, and other land uses (FAO, 2019). From 2001 to 2017, agriculture generated 5 billion tons of CO_2 equivalent (FAO, 2016, 2019). Globally, one third of the world's soils are degraded, releasing 78 gigatons of CO2 into the atmosphere and generating an economic cost of approximately 10% of GDP (FAO, 2019).

Among 184 countries, Peru ranks 129 based on its global participation of 0.44% of total GHG emissions in the various sectors (FAO, 2020). Land Use, Land Use Change and Forestry are the main emission sources in Peru, representing 45% of INGEI emissions (2014). Agriculture occupies the third position in terms of emissions (26,233 Gg CO_2eq, 16%).

Peru's agricultural sector contributes 5.6% to the Gross National Product (GNP) at the national level (Asencios et al., 2020). There are approximately 10 million people and 2.3 million agricultural units (AUs) involved in agriculture, a third of the Peruvian population (63% are mountain farmers, 20% are jungle, and 17% are coasters). Agriculture is also the second largest employer in the country after the service sector (CENAGRO, 2012). Peru's average productive land size is 4.8 hectares/AU, and 97% of its 2.3 million AU are family farms (CENAGRO, 2012; INEI, 2018). Small farms and family farms are the mainstays of Peruvian agriculture.

Sustainable food production is a challenge for small agriculture or family farming (Asfaw et al., 2015; Fernández et al., 2017; Miller et al., 2017). The challenges smallholder farmers face includes lack of inputs, limited market access, frequent pest and disease outbreaks, and other risks. Peruvian agriculture is also affected by climate change and variability. According to Branca et al. (2011), climate change affects small farmers disproportionately because of their low adaptive capacity and greater vulnerability.

As a result climate smart agriculture (CSA) can be an effective tool for transforming and reorienting agriculture under the new realities of climate change (FAO, 2010). The CSA approach addresses two global problems simultaneously, climate change and food security, by focusing on three pillars: achieving a sustainable increase in agricultural production while mitigating greenhouse gases (Amadu et al., 2020). For the formulation of development policies, the CSA approach can identify production systems that can respond better to climate change (Amadu et al., 2020).

As part of the CSA, sustainable practices include soil management, crop diversification, intercropping, rotations, cover crops, agroforestry, biological control of pests and diseases, plant-animal interactions, and agrobiodiversity management (Imran et al., 2018). Farmer management of agrobiodiversity is a critical element of CSA's approach since it allows us to fulfill human nutritional needs and maintain the natural balance of the planet (Asseffa, 2016). Teklewold et al. (2019) found that adopting CSA increased dietary diversity as well as increased calorie and protein availability. Therefore, this study addresses the relationship between CSA adoption and agrobiodiversity in small farmers. CSA options and agrobiodiversity are examined in this study in relation to economic variables in a local context. CSA and agrobiodiversity have a theoretical relationship that needs to be examined.

MATERIALS AND METHODS

Study area

The "Crisnejas" basin is included in the study area. The area covers 4,928 km^2, located between 78º38'2'' and -77º48'46'' west longitudes and parallels -8º0'55'' and -6º55'34'' south latitudes in the departments of Cajamarca and La Libertad (includes 9 provinces and 25 districts) (Figure 1). The multi-year average temperature is 8.5 °C, maximum 32.6 °C, and minimum -10.3 °C, with an average precipitation of 8,035 mm, ranging from 59 to 13,024 mm. The terrain is irregular with slopes ranging from 1,200 to 3,900 meters above sea level with great biological, climatic, and edaphic variability. Rivers Condebamba and Cajamarca form the basin on the Atlantic slope. Crisnejas basin is one of the country's poorest basins with 64.1% poverty rates, and most urban and rural people do not have access to water, drainage, or lighting (46.4%). In the basin, agriculture, livestock, hunting, and forestry account for 15.4% of GDP and oil, gas, and mineral extraction accounts for 30.5% (Minam, 2016). Agricultural landscapes in the basin are

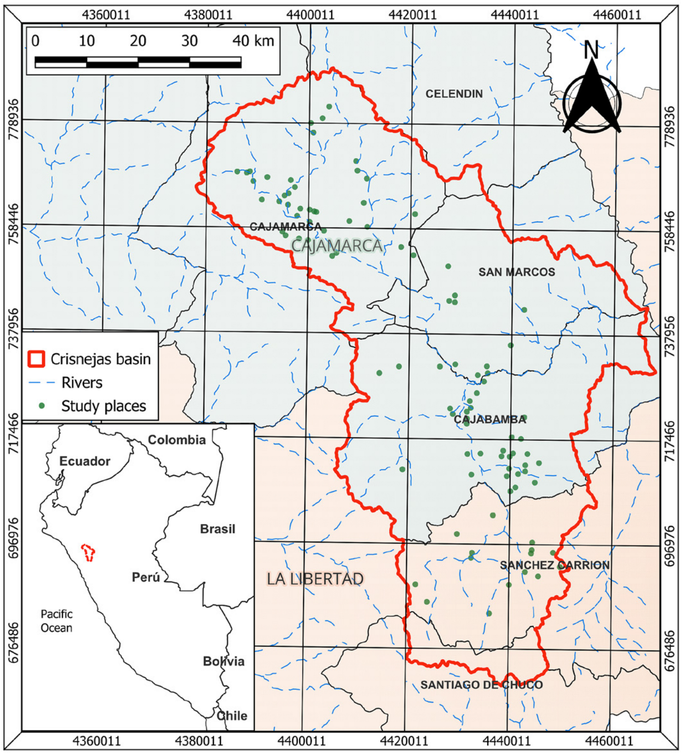

Figure 1. A description of the geographical location of the Crisnejas basin in the Andean region north of Peru. The map was created by the authors using QGIS version 3.32.2

dominated by family agriculture, with 96% of farmers owning smaller farms (45.8% of the total agricultural area) (CENAGRO, 2012). According to this last census 50.1% (43,342 AU) living in upper basin, 39.3% (34,044 AU) in the middle basin and 10.6% (9,144 AU) in lower basin.

Sample collection and analysis

By stratified sampling, 340 AU household heads were surveyed across 15 districts in the Crisnejas basin. In the basin, there are three strata: low zone (less than 2,500 meters above sea level), middle zone (between 2,500 and 3,000 meters) and high zone (over 3,000 meters). To collect data, a structured questionnaire was used to collect information on a wide range of topics, such as information on agrobiodiversity components (Leyva and Lores, 2018), household characteristics, characteristics of farmland, economic and social capital, market access, extension services, and training and CSA practices (Haq et al., 2021). Further information was gathered from the National Institute of Statistics and Informatics of Peru (INEI), Ministry of Environment, regional and provincial Agrarian Agencies (Cajamarca and La Libertad), as well as producer organizations in the "Crisnejas" Basin, including Cajamarca, San Marcos, Cajabamba, Santiago de Chuco, and Sánchez Carrión.

Characterization and classification of agrobiodiversity

In this proposal, recorded diversity is classified according to its importance: agrobiodiversity that is utilized for human consumption (IFER), animal welfare (IFE), soil protection (IAVA) and species that complement each other (ICOM); these four groups are also called index specific groups (GSI). The index IDA is expressed through the following mathematical function:

$$IDA = \frac{\sum_{1}^{S_t} V_i}{S_t(V_i max)} \tag{1}$$

where: V_i – measures the importance of each group of species in an AU, $V_i max$ – this value represents the maximum importance expected in the AU – every agroecological floor or location has its own expected value, S_t – based on Table 1, it represents the total number of species groups for each component.

In order to analyze each group individually, a specific index is developed (IGE), which considers its main functions within the agroecosystem:

$$\text{IGE}= \frac{\sum_1^{S_e} V_i}{S_e(V_i max)} \quad (2)$$

IDA integrates the four IGE subindexes as follows:

$$IDA = \frac{\sum_1^{n} S_e\,(IGE)}{S_t} \quad (3)$$

$$IDA = \frac{S_1\, IFER + S_2\, IFE + S_3\, IAVA + S_4\, ICOM}{S_t} \quad (4)$$

A structured questionnaire was used to collect information for IDA estimation. To determine the number of crops and the area occupied by crop groups, the areas occupied by each crop and its production during the last 12 months were considered. In the IFER subindex, animal production was quantified with its protein components expressed in meat production (animals for meat), milk (animals for milk), eggs (laying birds) and fish (freshwater fish species such as trout, paiche, others). Species-by-crop total production was quantified. The importance value (V_i) reflects the number of species estimated based on the agrobiodiversity record in each agricultural unit and the classification in Table 1. As a result, this study calculates IDA values ranging from 0 to 1. The maximum possible IDA value is 1.0, while an ADI value of 0.7 is considered sustainable.

Assessment of climate smart agriculture – multivariate probit model

Farmers often consider several options when making technology decisions, so their choice of one CSA option may impact their choice of another. Decisions are therefore necessarily multivariate (Aryal, Rahut, Maharjan, et al., 2018). Based on the multivariate probit model (MVP), it is possible to determine which CSA options are complementary (positive correlation) and substitutable (negative correlation).

A CSA option or practice is more likely to be adopted by a farmer if it has a greater benefit than its non-use. Suppose the i_{th} household (AU) (i = 1, 2, ..., N) is faced with a decision about applying the j_{th} CSA option (where "j" denotes the choice of one option, for example: minimum tillage (M), crop diversification (D), organic fertilizer (S) or mixed cultivation (O) in plot "p" (p = 1, ..., P). Furthermore, U_0 and U_j represent the benefits to a farmer without and with the adoption of CSA, respectively. The farmer decides to adopt the j_{th} CSA option on his plot "p" if its net benefit is greater than without it, i.e.:

$$B^*_{ipj} = U_j - U_0 > 0 \quad (5)$$

CSA's net benefit is a latent or unobservable variable, determined by the observed characteristics of the agricultural unit, economic variables, market access and extension

Table 1. Classification of groups of species according to their functions for the estimation of the IDA index

Sub-indexes	Item	Functional characteristics of species
IFER (Sub-index FER) Biodiversity for human nutrition	I	Animal origin (milk, meat, eggs, fish)
	II	Plant-based (legumes)
	III	Provides energy (roots, tubers, cereals, and Andean grains)
	IV	Providing energy (oil seeds)
	V	Regulating (vegetables)
	VI	Regulating (annual and perennial fruits)
IFE (Sub-index FE) Animal feed biodiversity	VII	A plant-based food (plants such as legumes, trees, and creepers)
	VIII	Provides energy (pasture, forage, and cereals)
IAVA (Sub-index AVA) Biodiversity to improve soils	IX	Green manures, crop residues, organic fertilizers, inert weeds (or non-crop species), live cover for soil protection
	X	Species that contribute to the production of biofertilizers
ICOM (Sub-index COM) Biodiversity for non-dietary purposes related to complementary and alternative function	XI	Species that have medicinal, stimulating, and seasoning properties
	XII	Flowers, ornamental plants, food plants for wild birds
	XIII	Use of timber for domestic purposes and the building of energy
	XIV	Uses not listed above include species with spiritual value, religious uses, industrial or artisanal uses
	XV	Solutions include climate change mitigation (living fences against the wind), repellents and attractants, hedges, and melliferous

Note: Adapted from Leyva and Lores (2018).

of services, and the plot, location (X_{ip}) and the error term (ε_{ip}) as follows:

$$B^*_{ipj} = X'_{ip}\beta_j + \varepsilon_{ip}\ (j = M, D, S, O) \quad (6)$$

There are several benefits associated with the net benefit B^*_{ijp}, including economic benefits, self-consumption, animal feed, and others. It is a latent variable, whose benefit is inferred from other variables observed in the model (through a mathematical model).

Equation (6) can be expressed as an indicator function. For each CSA option choice, the unobserved preferences in Eq. (6) are translated into the observed binary outcome equation as follows:

$$B_{ipj} = \begin{cases} 1\ if\ B^*_{ipj} > 0 \\ 0\ if\ B^*_{ipj} \leq 0 \end{cases} (j = M, D, S, O) \quad (7)$$

Multiple CSA options are available in the MVP with zero conditional mean and variance normalized to unity, that is, we can express it as (u_D, u_M, u_S, u_O) → ^{MVN}(0, Ω) and the covariance matrix (Ω) is given:

$$\Omega = \begin{bmatrix} 1 & \rho_{DM} & \rho_{DS} & \rho_{DO} \\ \rho_{MD} & 1 & \rho_{MS} & \rho_{MO} \\ \rho_{SD} & \rho_{SM} & 1 & \rho_{SO} \\ \rho_{OD} & \rho_{OM} & \rho_{OS} & 1 \end{bmatrix} \quad (8)$$

where: ρ – denotes the pairwise compensation coefficient of the error terms corresponding to either of the two CSA options.

For each individual CSA option, if the correlations on the off-diagonal elements are higher than 0, a multivariate probit is preferred instead of a univariate probit. Studied nine CSA options based on their resource use (water, carbon, nitrogen, and energy) (Table 2). It is assumed that decisions to adopt these CSA practices are interdependent.

Explanatory variables are shown in Table 3. According to Rojas-Downing et al. (2017a) household characteristics play a significant role in technology adoption decisions when market imperfections and institutional failures exist. Educational level and technology adoption are reported to be positively correlated (Aryal et al., 2018). Education improves access to information on improved technologies, so it is hypothesized that an AU headed by a literate person, at least with a primary education, would adopt an option CSA more likely. A household's literacy level can play a role in adopting agriculture-related technologies as part of an overall strategy to improve lifestyles and livelihoods.

New technologies are generally adopted more readily by households headed by men (Teklewold, Gebrehiwot, et al., 2019), even so, a recent study in India found that Aryal et al. (2018) found that women-headed households adopt climate-smart farming methods more often. According to the authors, female-headed households suffer from greater labor shortages.

A household's head of household's age is related to two issues: experience in farming and resistance to change (Aryaln et al., 2018; Makate et al., 2016). Since older people have more experience in agricultural systems, as well as accumulating physical and social capital, it is unclear how the age of the head of household impacts it. Additionally, they have shorter planning horizons, less energy, and a greater aversion to change, which makes them less likely to adopt new technologies.

Intensity of adoption of CSA – ordered probit model

Based on Teklewold et al. (2019), each plot's adoption intensity was determined by the number of CSA options adopted. The variable of interest takes integer values ranging from 0 to J, with J representing the number of CSA options selected. For this case, the dependent variable can take the values 2, 3, 4, up to 9 depending on whether a farmer applies a certain number of CSA options.

Table 2. Description of dependent variables used in this study – climate smart agriculture options

Variables	Description
Smart water	
Water management	1 if crop water use is conserved and controlled, "0" if not
Rainwater-sown crops	1 if you plant early in the season to take advantage of rainwater, "0" if not
Smart carbon	
Minimum tillage	1 cultivating land in a less disturbed manner than plowing "0" if not
Organic fertilizer	1 if use animal wastes, plant wastes from agriculture, "0" if not
Crop diversification	1 if planting different types of crops together, "0" if not
Crop rotation	1 if this land's crop type changes from season to season, "0" if not
Smart nitrogen	
Legumes	1 if you plant legumes between crops, "0" if not
Smart energy	
Compost	1 if you compost your waste after harvest, "0" if not

Table 3. Description of the explanatory variables used in the study

Variables	Description
Household (HH) characteristics	
HH gender (D)	2 if male and 1 if female
HH head's age (C)	Age of the head of household in years
Literate HH head (D)	2 if the head of UA is literate and 1 if not
Family size (C)	The number of family members (#)
Characteristics of farmland	
Plot tenure (D)	2 if owned and 1 if rented in
Fertile soil (D)	If the farmer reports fertile soil, 2 and otherwise, 1
Deep soil (D)	2 if deep and 1 if shallow
Gentle slope (D)	2 if the slope is gentle, and 1 if the slope is medium or steep
Plot distance (C)	House/home distance from plot (Km)
Irrigation access (D)	2 if the AU has access to irrigation and 1 otherwise
Irrigation type (D)	0 if it does not use irrigation, 1 if it is exudation, 2 if it is drip, 3 if it is sprinkling, 4 if it is multigates (pipes), 5 if it is sleeves and 6 if it is gravity
Economic and social capital	
Plot area (C)	Area of the plot (in hectares)
Land operated (C)	The total area of land operated (in ha)
Market demand (D)	2 if you consider that there is demand for your crops, 1 if not
Credit Access (D)	2 if the farmer has access to credit and 1 otherwise
Exchange (D)	2 if you share information (farmer to farmer), 1 if not
Association (D)	2 if they belong to farmers associations, 1 if not
Seed bank (D)	2 si almacena semillas para la próxima temporada, 1 si no
Agrobiodiversity (C)	Estimated value of the IDA for each AU
Market access, extension services, and training	
Market distance (C)	Distance to local market from home (in km)
Training (D)	2 if HH head participated in at least one training, 1 if not
Climate change (D)	The answer is 2 if they understand climate change, and 1 if you do not

Note: D – categorical variable; C – continuous variable, IDA – agrobiodiversity index, AU – agricultural units.

The ordered probit model (OPM) can be expressed as:

$$y^* = x'\beta + \varepsilon \quad (9)$$

where is not observed and is given by:

$$\begin{cases} y = 0\ if\ y^* \leq 0 \\ = 1\ if\ \ 0 \leq\ y^* \leq \alpha_1 \\ = 2\ if\ \ \alpha_1 \leq\ y^* \leq \alpha_2, \\ \quad\ldots \\ = J\ if\ \ \alpha_{J-1} \leq\ y^* \end{cases} \quad (10)$$

where: the values of are observed and known because they are the integer values of the number of CSA options that the family AUs are applying; and "α" is an unknown parameter to be estimated. "ε" is assumed to follow a normal distribution with zero mean and unit variance.

Therefore, the probability of each outcome can be expressed as follows:

$$\begin{aligned} &\Pr(y = 0|x) = \Phi\,(-\,x'\beta) \\ &\Pr(y = 1|x) = \Phi\,(\alpha_1 -\ x'\beta) - \Phi\,(-\,x'\beta) \\ &\Pr(y = 2|x) = \Phi\,(\alpha_2 -\ x'\beta) - \Phi\,(\alpha_1 -\ x'\beta) \\ &\ldots \\ &\Pr(y = J|x) = 1 - \Phi\left(\alpha_{J-1} -\ x'\beta\right) \end{aligned} \quad (11)$$

Data analysis

First, the data were compiled in an Excel spreadsheet, and then they were analyzed using Statistical Software Version 15 (STATA Corporation). The general characteristics of the AUs were described by means and standard deviation for the continuous variables (C); number of cases and percentages for categorical variables (D). With Shapiro-Wilk, the variables' normality was evaluated, and with Levene, the variance homogeneity was determined.

ANOVA (Kruskal-Wallis, non-parametric) was used to compare means of quantitative variables. Comparing constant data with normally distributed data was performed using the ANOVA test, and comparing constant data with non-normally distributed data was conducted using the Kruskal-Wallis test. Following this, a Dunn's posthoc test was carried out to assess the significance of the multiple comparisons. These tests were carried out to determine if there is a difference in IDA and income between altitudinal zones, irrigation conditions and the type of family farming. Statistical significance is defined as a p-value less than 0.05.

The National Institute of Statistics and Informatics of Peru (INEI) and the Ministry of the Environment provided secondary information as well as representative data from regional agrarian agencies (Cajamarca and La Libertad) as well as provincial ones (Cajamarca, San Marcos, Cajabamba, Santiago de Chuco and Sánchez Carrión).

RESULTS AND DISCUSSION

This study located the AUs relative to their altitudinal parameters between 1,131 meters and 3,257 meters above sea level. In addition, 26.5% (90/340) of the AUs were in the low zone (2,500 masl.), 45.6% (155/340) were in the middle zone (2,500–3,000 masl.), and 27.9% (95/340) were in the upper zone (> 3,000 masl.). Heads of households surveyed were on average 44.1 years old. The average household has five members. A total of 91.1% (n = 30) of interviewed family heads were males, while 8.8% (n = 30) were females. In the study area, AUs cultivate an average of 4.15 hectares, ranging from 0.5 ha (minimum) to 9 ha (maximum). Based on these characteristics, all AUs surveyed are family AUs as defined by the National Plan for Family Agriculture.

Agrobiodiversity analysis

In general, the agrobiodiversity index (IDA) obtained shows an average value of 0.56, with a maximum value of 0.83 and a minimum value of 0.37 (Figure 2 and Table 4). In accordance with Leyva and Lores (2012), a value of less than 0.7 indicates a deficient agro-biodiverse system because the family AUs do not manage the groups of species to maintain the ecological balance.

As can be seen from Table 4, disaggregated analyses of IDA by subindices clearly highlight that biodiversity intended for human consumption (IFER) and animal consumption (IFE) are prioritized. IFER/IFE values (0.58 and 0.61, respectively) are statistically higher than IAVA and ICOM (0.51 and 0.50) (t-student test, p-value < 0.05). So, it is imperative that the planning and integration of the various components are improved, with a particular emphasis on improving the soil's physical, chemical, and biological properties (IAVA) and complementary biodiversity of non-food utility (ICOM), which has a lower value in the basin. There were no statistically significant differences between IFER and IFE (t-student, p-value = 0.0904).

The index IDA is greater in the lower and middle zones of the basin (Table 4) and statistically significant (ANOVA test, p-value = 0.001) (Figure 3). A statistical difference is observed between the low and middle zone (ANOVA, p-value < 0.0001), and between the middle and upper basin (ANOVA, p-value < 0.0001). The climatic conditions and irrigation access in the lower and middle zones of the basin favor greater biological diversity.

In agreement with other authors, these results indicate producers manage diversity based on the family's economic needs (González et al., 2018; Leyva and Lores, 2018; Leyva Galán and Lores Pérez, 2012). They suggest that families prioritize cultivating species that have nutritional or practical economic value. Agroecosystem diversity in the basin is mainly dominated by species directly related to human and animal nutrition. It is evident that this context is influenced by the economic philosophy of the family AUs, who have agriculture as their primary source of income. Household heads showed no interest in planting crops that provide no benefit other than economic or nutritional benefits to their families.

Table 4 presents the analysis of monthly income in the AUs. Income and agrobiodiversity

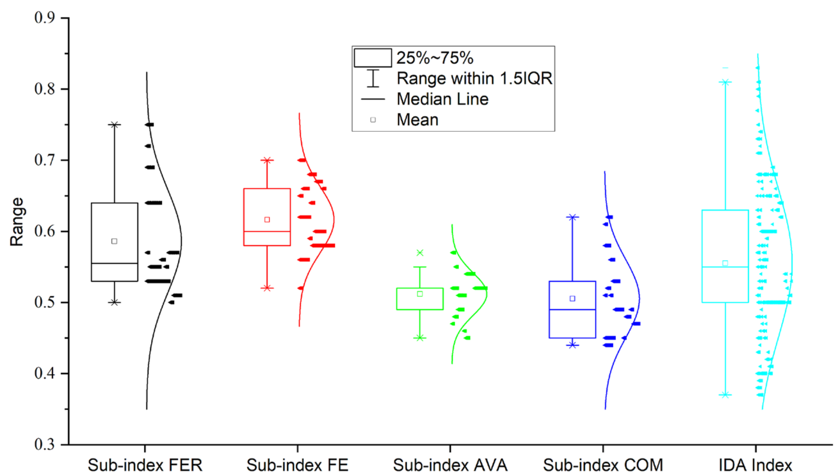

Figure 2. Graphical representation of the agrobiodiversity index and its specific components (IFER, IFE, IAVA, and ICOM) measured in the Crisnejas basin. In each case, the error bar represents the range between the maximum and minimum value. The image was created by the authors using OriginPro 2018

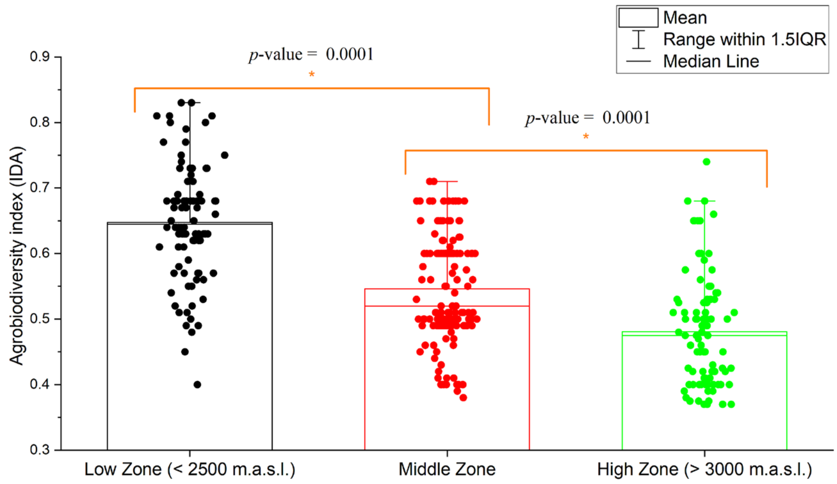

Figure 3. Agrobiodiversity index distribution by zones in the Crisnejas basin measured in family agricultural units. ANOVA/Kruskal-Wallis test for comparing groups, p-value < 0.05 is statistically significant. The image was created by the authors using OriginPro 2018

index (IDA) are negatively related, meaning that AUs with lower agrobiodiversity have higher incomes. A significant negative correlation can be observed (CI = -0.4107) based on the Pearson binary correlation method (Table 4).

Moreover, Table 4 shows that the negative correlation with IDA varies across classification groups. Based on the type of family farming, for instance, there is a non-significant correlation between subsistence family farming (<2 ha) and intermediate family farming (2–5 ha) based on these findings, which implies that no correlation exists and has been assumed to have a zero-correlation coefficient. However, in the case of consolidated family agriculture (5–10 ha), the negative correlation is significant, meaning that the highest incomes are concentrated in AUs with the lowest agrobiodiversity index. In the group "according to irrigation condition", it can be observed that AUs cultivating "dryland/irrigation" have a stronger negative correlation than AUs cultivating "dryland" and "irrigation" separately.

According to altitudinal zone classification (high, low, medium), the negative correlation is also significant, indicating that AUs with lower altitudes have greater agrobiodiversity and lower income. The means of IDA (ANOVA, p-value 0.001) and the average income (ANOVA, p-value 0.0001) are statistically different between the basin zones. Comparatively, the low zone has the

Table 4. Correlations between agrobiodiversity index (IDA) and monthly income of AUs in Crisnejas

Groups	IDA[ȣ]	Income[ȣ] (USD)	Correlation coefficient (IDA vs income)
IDA and monthly income AU (global)	0.56	312	-0.4107*
According to family farming (FF)			
Subsistence FF (<2 ha), n = 133	0.60	186	-0.1092
Intermediate FF (2–5 ha), n = 54	0.58	298	-0.1570
Consolidated FF (5–10 ha), n = 153	0.51	428	-0.2699*
Irrigation condition			
Rainfed	0.47	202	-0.2882*
Rainfed / irrigation	0.59	280	-0.7024*
Irrigation	0.61	365	-0.5225*
Altitudinal zones			
Low zone (< 2,500 masl.)	0.65	246	-0.5773*
Middle zone (2,500–3,000 masl.)	0.55	352	-0.3551*
High zone (> 3,000 masl.)	0.48	312	-0.2351*

Note: (*) Pearson binary correlations with p-value < 0.05. (ȣ) ANOVA/ Kruskal-Wallis test to compare means, statistical significance with a p-value < 0.05. AU = agricultural unit.

highest IDA value (Table 4) and has the lowest average income. Recent studies have shown that species numbers decline with increasing altitude, and this is due to decreases in temperature, precipitation, and soil fertility (Adhikari et al., 2017; Körner, 2007; Timsina et al., 2016). Körner (2007) says every 100 meters of altitude reduces the diversity of angiosperms by 40 species. A significant decrease in agrobiodiversity associated with higher altitude has also been observed in the Crisnejas basin, despite only recording species related to agriculture.

In summary, the highest economic-income AUs are located between 2,500 and 3,000 meters above sea level, have access to irrigation, and are also part of consolidated family farms (Table 4). According to these results, agricultural biodiversity must be increased equitably to convert the agroecosystem into a functional and balanced system, from an economic, ecological, and sociocultural perspective.

Assessment of climate smart agriculture

AUs in the study area have adopted at least two CSA options simultaneously, suggesting a correlation between their CSA choices. Based on the MVP, the results support the hypothesis that the error terms of multiple decision equations are correlated. The likelihood ratio test (chi^2 (36) = 66.043; Prob > chi^2 = 0.0017) rejects the null hypothesis of zero covariance of the error terms between equations. This statistical evidence supports the estimation using the MVP, AUs adopt the CSA options in packages, which agrees with what was reported by Teklewold, Mekonnen, et al. (2019). Furthermore, Aryal et al. (2018) argue that farmers should adopt attractive practices first and then adopt other options sequentially if they provide complementary features.

The results of the maximum likelihood estimation of the MVP are presented in Table 5. Based on the Wald test, the parameters estimated in the model fit the data well (Wald chi^2 (243) = 391.26; Prob. > chi^2 = 0.0000) rejecting the null hypothesis that all coefficients of regression are equal to zero. This statistical evidence demonstrates the importance of the multivariate probit model (MVP) to account for unobserved correlations between decisions to apply multiple CSA options in AUs. To facilitate interpretation, Table 5 highlights only statistically significant values that indicate positive (+) or negative (-) associations with multiple CSA adoption.

Some of the CSA options are negatively and positively affected by the altitude variable. In households located at higher altitudes (masl.), agricultural water management techniques such as conservation and controlled use of water (CW); sowing mixed crops (CM) and composting (COM) are more likely to be practiced. In contrast, at high altitudes, organic vegetable fertilizer (AOV) and crop rotation are less likely to be used (Table 5). The management of agricultural water is one of the best strategies for adapting to climate change in agriculture (Teklewold, Mekonnen, et al., 2019).

AUs in the Crisnejas basin use water management techniques at a higher altitude, but the analysis by zones indicates that an inverse relationship exists in the high zone (>3,000 masl), i.e. AUs are less likely to use water management techniques in the high zone. This is explained because the availability of water in the high area is limited and is mainly characterized by dry agriculture. AUs located in the middle basin (2500-3000 masl) are more likely to use organic vegetable fertilizer (AOV) and rotate crops per season (RC) than those in the lower basin. Compared to the lower zone, there's less likelihood of using water management techniques in the upper basin (above 3000 masl). Rainwater (URW) is more likely to be used at the beginning of the season in the high zone and middle zone. Rainfall and water availability are key factors in determining CSA adoption, according to these results.

Regarding the gender variable, this thesis shows that households headed by men are more likely to adopt water management techniques, similar to the findings of other studies on small farmers (Ardakani et al., 2019; Chandra, 2017). The adoption of organic fertilizers is more common in households headed by females than in households headed by males (Kpadonou et al., 2017). To shed more light on evidence of the female role in the adoption of technologies reported in the literature, a more in-depth analysis is needed with a larger number of households headed by women. Adoption of the other CSA options is not affected by gender differentiation.

Older household heads are more likely to use organic animal fertilizer in their crops (AOA) and apply minimum tillage and/or zero tillage (ZT/MT). Maguza-Tembo et al. (2017) note that older household heads are less familiar with relatively new and/or alternative technologies.

Regarding the characteristics of the land, tenure affects adoption: AUs with their own land are

Table 5. Key determinants of CSA adoption in Crisnejas

Variables	CW	URW	ZT/MT	AOV	AOA	CM	RC	SL	COM
Household (HH) characteristics									
Altitude (masl)	+			-		+	-		+
Zones									
Low (reference)									
Middle		+		+			+		-
High	-	+							
Age (years)			+		+				
Gender									
Female (reference)									
Male	+								
Family size									
Literacy									-
Characteristics of farmland – Farm ownership									
Rented (reference)									
Owned	+								
Soil fertility					+			-	
Soil depth									
Slope	+								
Farm distance (km)							+	-	
Irrigation access									
Rainfed (reference)									
Rainfed/irrigated									-
Irrigation					-				-
Economic and social capital									
Plot area (ha)						+			
Land operated (ha)									
Market demand							+	+	
Credit access									
Exchange									
Association									
Seed bank									
Certified seeds		+							
IDA Index					+				+
Income									
Market access, extension services, and training									
Market distance									
Training					-				
Climate change		-							

Note: *RCW: regulates or controls water use, URW: Uses rainwater, ZT/MT: Minimum, AOV: Uses organic vegetable fertilizer, AOA: Uses organic animal fertilizer; CM: Crop diversification, RC: Crop rotation, SL: Sowing legumes, COM: Composting. (+) and (-) represents a significant association that can be positive or negative.

more likely to apply some water management technique such as water collection and/or conservation through wells or micro reservoirs (RRW). Previously published studies have also reported a positive association between tenure and CSA (Ardakani et al., 2019). The benefits of implementing CSA accrue over time and may continue to be used by the AU, whereas leasing is not guaranteed to yield a long-term benefit.

Farms with a conception of land fertility tend to apply organic animal fertilizer (AOA), whereas farms with a conception of not being very fertile tend to plant legumes (SL). In farms with a higher slope, water management techniques are more likely to be applied. The larger the plot area, the higher the probability of adopting CM. AUs with larger farms usually raise more animals and plant crops specifically for feeding their livestock and animals, so they are more likely to use organic fertilizer. They use their own fertilizer as well as commercial fertilizer.

The planting demand is positively impacted by legumes (SL) and CR adoption, findings published previously as well (Bedeke et al., 2019; Bell et al., 2018). A farmer's priority is to grow crops that sell at the best price and can be sold from season to season. In previous studies, CR has been shown to reduce the incidence of weeds and pests, minimize disease risks (Imran et al., 2018; Wekesah et al., 2019) and improve soil fertility (Di Falco and Zoupanidou, 2017). Long-term benefits include less variation in yield and less risk of poor harvests (Di Falco and Zoupanidou, 2017). The average monthly income of the AUs, estimated from their resources for sale and self-consumption, does not show statistical association with any of the CSA options.

Households exposed to agricultural extension services are less likely to adopt practices of using organic animal manure (AOA), indicating that the information does not lead to CSA adoption. Even though 13% of the AU received some agriculture training, this does not indicate that CSA practices are being adapted positively. Trainings have, on the other hand, decreased the use of AOA, suggesting that other types of inorganic fertilizers are preferred, which are widely used in the basin and are promoted at the national level.

Agrobiodiversity measured with the IDA is positively associated with the generation of organic fertilizer through COM and the use of animal organic fertilizer. None of the other CSA options have a significant association. Composting is easier in AUs with a greater diversity of plants and animals. However, the level of agrobiodiversity in the basin on average is low, becoming inefficient and distant from agroecological sustainability.

Intensity of adoption of climate-smart agriculture

An analysis of the elements and factors that influence an AU's decision to adopt a particular CSA practice was presented in the previous section, considering that this decision may involve adopting one or more practices. This analysis, however, does not explain why farmers combine several of these CSA options. Table 6 presents an analysis of the determinants of CSA adoption intensity, defined as the number of practices adopted.

The study area has adopted multiple CSAs, although the intensity of adoption varies. An ordered probit model was estimated to evaluate the factors influencing the adoption of CSA options. The maximum number of CSA options per household is nine (Table 6). The chi-square statistic for the calculated econometric ordered probit model is statistically significant (LR chi^2 (25) = 82.47; Prob > chi^2 = 0.000) and rejects the null hypothesis (all slope coefficients are equal to zero) (Table 6).

Some factors influence the number of CSA practices used by AUs, according to the results. As shown in Table 6, the characteristics of the middle zone of the basin, the head of household's age, land ownership, market demand, and higher economic income favor the intensification of CSA practices in the plots.

CSA practices are more likely to be intensified in households located in the middle zone of the basin than in households located in the lower zone. Additionally, land tenure was highly significant, suggesting that secure land tenure is an incentive factor for intensifying and investing more in CSA practices. Ardakani et al. (2019) report that age plays an important role in applying a greater number of CSA options. Economically, richer households, i.e., those with higher incomes, are more likely to adopt CSA practices. Intensification of CSA practices is positively impacted by market demand.

An analysis of data separating and grouping the data based on basin areas was conducted since altitude is one of the determining factors in the intensity of CSA adoption (Table 7).

Family size determines the intensity of CSA adoption in the lower basin. As the distance to the farms increases, the probability of adopting one, two, three, and five CSA options decreases. Land fragmentation may also limit CSA adoption: the probability of adoption is higher for CSA options with one to eight options, which indicates a positive association between larger parcel sizes and adoption intensity (Table 7).

Compared to household heads without literacy skills, household heads with incomplete and complete secondary education are more likely to adopt at least two, five, and seven CSA options in the middle zone. Distance to market significantly

Table 6. Estimates of the ordered probit model

Variables	Coefficient	Standard error	P > |z|	[95% IC]
Household (HH) characteristics				
Altitude (masl.)	0.0003	0.0003	0.288	0.000-0.001
Zones				
Low (reference)				
Middle	0.7050	0.2395	0.003*	0.236-1.174
High	0.4611	0.3214	0.151	-0.169-1.091
Age (years)	0.0127	0.0051	0.012*	0.003-0.023
Gender				
Female (reference)				
Male	-0.0511	0.2048	0.803	-0.452-0.350
Family size	0.0114	0.0230	0.620	-0.034-0.056
Education level, HH head				
No education (reference)				
Initial	-0.2387	0.2174	0.272	-0.665-0.187
Incomplete primary	-0.2053	0.2242	0.360	-0.645-0.234
Complete primary	-0.1279	0.2064	0.536	-0.532-0.277
Incomplete secondary	-0.2118	0.2111	0.316	-0.626-0.202
Completed secondary	-0.2867	0.2160	0.184	-0.710-0.137
Higher non-univ. Income.	-0.2726	0.3723	0.464	-1.002-0.457
Characteristics of farmland – Farm ownership				
Rented (reference)				
Owned	0.4202	0.2292	0.007*	0.029-1.869
Soil fertility	0.2576	0.2053	0.210	-0.145-0.660
Soil depth	-0.1751	0.2056	0.395	-0.578-0.228
Slope	-0.0418	0.1707	0.806	-0.376-0.293
Farm distance (km)	-0.0148	0.0332	0.655	-0.080-0.050
Irrigation access				
Rainfed (reference)				
Rainfed/irrigated	0.3512	0.2240	0.117	-0.088-0.790
Irrigation	0.3384	0.2319	0.145	-0.116-0.793
Economic and social capital				
Plot area (ha)	0.2292	0.1446	0.113	-0.054-0.513
Land operated (ha)	-0.1528	0.1329	0.250	-0.413-0.108
Market demand	0.3780	0.1850	0.041*	0.015-0.741
Credit access	-0.0583	0.2147	0.786	-0.479-0.362
Exchange	-0.0325	0.1289	0.801	-0.285-0.220
Association	0.3468	0.3164	0.273	-0.273-0.967
Seed bank	0.1984	0.2788	0.477	-0.348-0.745
Certified seeds	0.3468	0.3686	0.347	-0.376-1.069
IDA Index	0.6134	0.9259	0.508	-1.201-2.428
Income	0. 3456	0.0002	0.017*	-0.001-1.220
Market access, extension services, and training				
Market distance	-0.0204	0.0231	0.377	-0.066-0.025
Training	-0.2280	0.2043	0.264	-0.629-0.172
Climate change	-0.2747	0.1689	0.104	-0.606-0.056
Statistics for the model				
Number of observations				340
LR chi^2 (25)				82.47
Prob > chi^2				0.0000
Log likelihood				-525.08331

Table 7. Summary of the key determinants for the intensity of CSA adoption in the zones of the Crisnejas basin

Variables	Low zone (<2500 masl.)	Middle zone (2500–3000 masl.)	High zone (>3000 masl.)
Household (HH) characteristics			
Altitude (masl.)			
Age (years)			
Gender			
Female (reference)			
Male			
Family size	+		
Education level, HH head			
No education (reference)			
Initial			
Incomplete primary			
Complete primary			
Incomplete secondary		+	
Completed secondary		+	
Higher non-univ. Income.			
Characteristics of farmland			
Farm ownership			
Rented (reference)			
Owned			
Soil fertility			
Soil depth			
Slope			
Farm distance (km)	+		
Irrigation access			
Rainfed (reference)			
Rainfed/irrigated			-
Irrigation			
Economic and social capital			
Plot area (ha)	-		
Land operated (ha)	+		
Market demand			-
Credit Access			
Exchange			
Association	-		
Seed bank	-	+	
Certified seeds			
IDA Index	-		
Income			+
Market access, extension services, and training			
Market distance			+
Training			
Climate change			

Note: (+) and (-) represent significant associations that can be positive or negative.

influences the adoption intensity of one, two, three, and five CSA options in the upper basin. However, the increase in demand and availability of water decreases the probability of adoption of six, seven, and eight CSA options (Table 7).

Based on all these results, based on the MVP analysis, each type of climate-smart agricultural practice presented a heterogeneous association within this study. Water and altitude availability, among other factors, determine largely whether CSA is adopted.

As one of the best strategies to adapt agricultural production to climate change and variability in conditions, agricultural water management practices improve the balance, availability, infiltration, and retention of water in the soil; reduce water loss through runoff and evaporation; and enhance the quality and availability of groundwater and surface water (Amadu et al., 2020). An approximate 10% of the AUs in the basin have small reservoirs, which are accompanied by irrigation, drainage, and water control techniques, achieving stability. To ensure crop growth, soil conditions must be kept close to optimal. According to Kpadonou et al. (2017) this water management practice is suitable to respond to the key agroecological constraints of low rainfall patterns and warmer climate conditions.

In the Crisnejas basin, crop rotation, or crop diversification, is a traditional practice in the family AUs. It is one of the most popular CSA options in the basin (89.7% AUs) and improves soil fertility and water retention capacity (Teklewold et al., 2013). A further economic benefit of CR is that it stabilizes agricultural income over time by balancing the impact of price fluctuations (Ghimire et al., 2022; Hrabanski and Le Coq, 2022). A family AU tends not to apply RC if water is available for irrigation, resulting in negative long-term effects on soil fertility. Evidence from MVP indicates that crop rotation is associated with temporary market demand, i.e., it is used to plant crops with a higher value.

In this study, minimum tillage (ZT/MT) is understood as reduced tillage (only one plowing pass) or zero tillage, which is defined as cultivating without disturbing the soil. Around 7% of family AUs in the basin practice this practice. Tractors have largely replaced this traditional practice. Agricultural agencies estimate that 90% of AUs use tractors. Unfortunately, the inherent benefits of ZT/MT have been neglected, as it can simultaneously achieve both adaptation and mitigation objectives, by improving soil health, improving soil aeration, sequestering carbon, and improving soil fertility and water retention capacity (Aryal et al., 2015).

In the basin, organic fertilizer is mainly of animal origin (AOA) and refers to livestock waste applied to crops. In recent years, animal waste types have diversified, resulting in a greater use of chicken manure. Climate change can be mitigated and adapted through organic fertilizer use. Providing nutrients, especially nitrogen (N), phosphorus (P) and potassium (K), will contribute to long-term soil fertility maintenance (Enahoro et al., 2018). Although this practice is applied in 83.5% of AUs, the majority also complement using inorganic fertilizers such as urea (the most popular fertilizer) and other inorganic fertilizers.

Lastly, adopting CSA options was linked to the highest level of agrobiodiversity. This component of agroecosystems can buffer negative environmental effects and can support the resilience of AUs, although, however, we did not find a positive correlation with income generation. Consequently, diverse agroecosystems (higher IDA) seem more suitable and capable of dealing with climate variability and other sources of climate change impacts.

CONCLUSIONS

Based on 340 familiars agricultural (smallholder farmer) household heads in 15 districts of northern Peru (Crisnejas basin), we found that the general agroecological diversity index showed a low level of agrobiodiversity and a distance from agroecological sustainability (IDA = 0.56). Increasing biodiversity equitably associated with agriculture is emphasized, focusing on converting the agroecosystem into an economically, ecologically, and sociocultural balanced system. As part of the IDA for the Crisnejas basin, species related to food for humans and animals were prioritized (IFER = 0.58 and IFE = 0.61). However, the diversity linked to laned care and maintenance (IAVA = 0.51) as well as complementary biodiversity with a food function (ICOM = 0.50) were undervalued. Those with a lower agrobiodiversity index earn a higher monthly income than those with a higher agrobiodiversity index have a higher monthly income (IDA = 0.56, 312 USD, Pearson binary correlation significative, CI = -0.0.4107, p-value < 0.05). Moreover, family farms with the highest economic incomes are located between 2,500 and 3,000 meters above sea level (middle zone, 352 USD, CI = -0.3551, p-value < 0.05), have access to irrigation (365 USD, CI = -0.5225, p-value < 0.05), and belong to consolidated family farms (365 USD, CI = -0.5225, p-value < 0.05). In general, household heads did not plant crops that didn't benefit their families economically or nutritionally.

Climate-smart agriculture factors and adaptation practices were identified using multivariate probit and ordered probit random effects models. These results indicate that the practices used in CSA are highly complementary (chi^2 (36) = 66.043; Prob> chi^2 = 0.0017), It means that the farmers in the Crisnejas basin adopted these practices as complementary practices (packages or group); their decision to apply an CSA option depended on the decision to use another option. Households located at a higher altitude have a greater probability of applying agricultural water management techniques through conservation and controlled use of water, sowing mixed crops and composting (coefficient positives with p-value < 0.05). However, at higher altitudes, there is less probability of using organic vegetable fertilizer (AOV) and crop rotation (coefficient negatives, p < 0.05). Other factors such as gender, education, age, land tenure, soil fertility, distance to market, irrigation, demand, and CSA have statistically significant effects on the decision to adopt CSA practices in AUs. Currently, the training has no positive effect on farmers' CSA. To combat climate change, communication tools should also be used to share and promote knowledge about CSA.

CSA practices are intensified in the plots due to the characteristics of the middle zone of the basin (p = 0.003), the head of household's age (p = 0.012), land ownership (p = 0.007), market demand (p = 0.041), and higher monthly economic income (p = 0.017). In the lower basin, family size, distance from farms, and cultivated area determine the intensity of ACI adoption. Compared to household heads who cannot read or write, education is the primary intensification factor in the middle zone. Monthly income and distance to market positively affect the intensity of ACI adoption of one, two, three, and five options in the upper basin. According to these findings, the factors are diverse and farmers in different zones face different conditions.

Agrobiodiversity also strengthened AUs' resilience to climate change by buffering negative environmental effects. Climate-change adaptation plays an important role in addressing Peruvian agriculture's vulnerability to climate change, but family households need broader reforms and policies to take advantage of CSA.

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