Mitigating the impact of El Niño-related drought on smallholder farmers in Central Sulawesi, Indonesia: An interdisciplinary modelling approach combining linear programming with stochastic simulation

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Abstract

Crop production in the tropics is subject to considerable climate variability caused by the El Niño-Southern Oscillation (ENSO) phenomenon. In Southeast Asia, El Niño causes comparatively dry conditions leading to substantial declines of crop yields with severe consequences for the welfare of local farm households. Using an interdisciplinary modelling approach that combines regression analysis with linear programming (LP) and stochastic simulation and integrates climatic and hydrologic modelling results, the objective of this paper is to assess the impact of El Niño on agricultural incomes of different types of smallholder farmers in Central Sulawesi, Indonesia, and to identify suitable crop management strategies to mitigate the income depressions.

We identify five farm classes by cluster analysis. Our LP-model maximizes their cash balance at the end of the period most severely affected by El Niño. Main activities are the cultivation of rice, maize, and cocoa; including water supply as an input factor, external Cobb-Douglas production functions generate output according to level of production intensity and predicted weather patterns. Stochastic simulation accounts for variations in crop yields due to factors not captured by the production functions. Iterative model runs produce probability distributions of the model outcomes for each household class, whereby the downside risk of failing to achieve a specified minimum level of income is particularly insightful. The results can contribute to the formulation of enhanced development policies by illustrating that drought-related crop management recommendations must be tailored to farm households according to their location, farming system, and resource endowment.

Keywords: ENSO, risk management, linear programming, stochastic simulation, Indonesia.

1 Introduction

Crop production in the tropics is subject to considerable climate variability that is mostly attributable to the El Niño - Southern Oscillation (ENSO) phenomenon (Salafsky 1994; Amien *et al.* 1996; Datt and Hoogeveen 2003). In Southeast Asia, El Niño is associated with comparatively dry conditions: ninety-three percent of droughts in Indonesia between 1830 and 1953 occurred during El Niño years (Quinn *et al.* 1978). In four El Niño years between 1973 and 1992, the average annual rainfall amounted to only around 67% of the 20-year average in two major rice growing areas in Java, Indonesia, causing a yield decline of approximately 50% (Amien *et al.* 1996). There is strong evidence that, in concert with global warming, the frequency and severity of extreme climatic events will increase during the 21st century, and the impacts of these changes will notably hit the poor (Easterling *et al.* 2007: 283-284).

Several macro-scale studies model the impact of climate variability and climate change on crop production in the Asia-Pacific region (see Zhao *et al.*, 2005, for a review). However, in order to evaluate specific climate variability impacts and corresponding optimal agricultural adaptation strategies, it is necessary to study the associated systems at the community and household levels. The Intergovernmental Panel on Climate Change identified the "quantitative assessment of the sensitivity, adaptive capacity, and vulnerability of natural and human systems to […] climatic variation" as one of the high research priorities with respect to policymaking needs (McCarthy *et al.* 2001: 17). Against this background, the objective of this paper is (1) to quantify the impact of ENSO-related drought on crop yields and, hence, agricultural incomes in a rainforest margin area in Indonesia, (2) to identify suitable crop management strategies for different climate scenarios using linear programming (LP), and (3) to account for agricultural production risks by combining the LP-model with stochastic simulation of random yield fluctuations. By doing so, instead of deriving point estimates, we produce more realistic probability distributions of the model outcomes, whereby the downside risk of failing to achieve a specified minimum level of income provides a particularly insightful measure of vulnerability.

The remainder of the paper is structured as follows: a brief description of the research area is provided in section 2; section 3 develops our methodological approach, while section 4 describes the data used and the model applied in detail; modelling results are presented in section 5; in section 6 results are discussed and conclusions drawn.

2 Description of the research area

The research area encompasses the Palu River watershed in Central Sulawesi province, Indonesia. Its mountainous topography, ridges reach up to 2,500 m a.s.l.[1], results in a distinct rainfall gradient, with the coastal zone receiving only around 500 mm of rain per annum, while precipitation exceeds 3,000 mm at higher elevations (WWF 1981). Due to the complex

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[1] Metres above sea level.

local climate patterns the manifestation of El Niño-related drought varies depending on the specific location. In our modelling approach, we therefore differentiate between the three sub-districts of Sigi Biromaru (50 – 90 m a.s.l.), Palolo (550 – 650 m a.s.l.), and Kulawi (560 – 980 m a.s.l.), which feature diverging climatic and hydrologic characteristics. Agricultural land use is also very location specific, depending on local rainfall, topography and soil properties. Overall, irrigated rice and cocoa are the two dominant crops grown, with mean farm-level area shares of 36% and 31%, respectively. Rice, with an average gross margin of 2.4 million IDR[2] per ha and cropping season, is used both for own consumption and sale; cocoa is a particularly important source of income with a mean gross margin of 9.3 million IDR per ha and year.

Figure 1 illustrates the ENSO-related variability of monthly rainfall in Central Sulawesi, showing that the June – October period is particularly affected; in the observed El Niño years rainfall is reduced to 62% of the average during this period. Moreover, the distribution of rice planting times is displayed: while there are no clearly defined planting periods in the equatorial climate, the distribution peaks in January/February for the first and in June to August for the second rice crop. Hence, in general, the El Niño-related depression in rainfall largely coincides with the second cropping season.
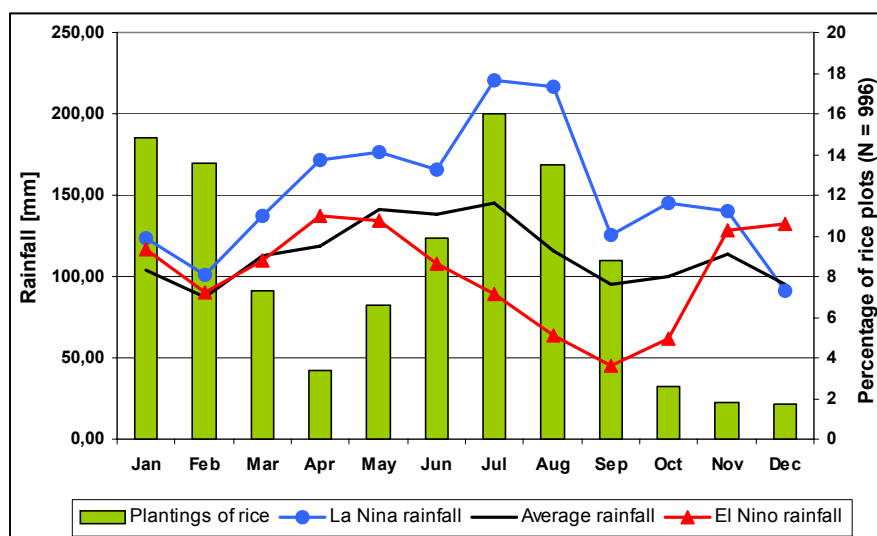
Figure 1. ENSO-related variation of monthly rainfall and temporal distribution of rice plantings in Central Sulawesi. Sources: Own survey (plantings); Dinas Pertanian Kabupaten Donggala (rainfall).

Note: Rainfall data are averages from 24 rain gauges throughout Central Sulawesi for the period 1981 to 1999, whereby 1982, '87, '91, and '97 are considered as El Niño, and 1988, '96, and '98 as La Niña years.

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[2] Indonesian Rupiah. 1 USD = 8,900 IDR (February 2003).

3 Methodology

3.1 ENSO scenarios used in the simulation model

Based on existing time series data of rainfall in Central Sulawesi we calculate the monthly precipitation anomaly of ENSO years in percent relative to the long-term mean and generate two graded ENSO scenarios which reflect the mean anomaly of all observed ENSO events (1987, 1991, 1994, and 1997) on the one hand, and the extreme ENSO event of 1997 on the other. Applying interpolation techniques, rainfall deviations in the two scenarios are calculated for the research villages, whereby the non-ENSO year 2003[3] serves as a reference year for 'normal' meteorological conditions (Gunawan 2006).

In the case of irrigated rice water is not only supplied through rainfall, but, most importantly, through irrigation water. As a proxy of the amount of irrigation water available in a given village, the total discharge ($m^3 d^{-1}$) in the corresponding sub-catchment during the vegetation period is calculated based on ENSO scenario simulation results of the hydrological model WASIM-ETH; the total discharge is then divided by the total area of irrigated rice[4], resulting in the specific discharge (mm) available for irrigation in each research village (Leemhuis 2006). Table 1 summarizes the characteristics of the three sub-districts of the research area in terms of rainfall and available irrigation water for the three scenarios 'Normal', 'Average ENSO', and 'Severe ENSO'.

Table 1. Rainfall and available irrigation water in Central Sulawesi during the period June 01 to Nov 30 for three climate scenarios, differentiated by sub-district

Climate scenario and sub-district	Rainfall [mm] (% of 'normal' in brackets)	Irrigation water [mm] (% of 'normal' in brackets)
,Normal' year[a]:		
Sigi Biromaru	539 (100)	7,872 (100)
Palolo	1,379 (100)	2,904 (100)
Kulawi	1,134 (100)	6,110 (100)
Average El Niño scenario[b]:		
Sigi Biromaru	341 (63)	4,286 (54)
Palolo	675 (49)	847 (29)
Kulawi	790 (70)	4,568 (75)
Severe El Niño scenario[c]:		
Sigi Biromaru	248 (46)	3,751 (48)
Palolo	627 (45)	808 (28)
Kulawi	565 (50)	3,407 (56)

[a] ,Normal' refers to the non-ENSO year 2003.
[b] Based on the mean of the El Niño years 1987, 1991, 1994, 1997.
[c] Based on the El Niño year 1997.

Due to its location in the rain-shadow of two mountain ranges, the low-lying sub-district of Sigi Biromaru receives significantly less rainfall than the other two sub-districts. However,

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[3] Based on the Southern Oscillation Index. Source: BOM (2007) Australian Government Bureau of Meteorology. http://www.bom.gov.au/climate/current/soi2.shtml, accessed on 23.03.2007.

[4] The calculation of the irrigated rice area is based on the Landsat/ETM+ classification of the year 2002.

because of the size of the sub-catchment, the amount of available discharge water is high. Between Palolo and Kulawi there are only relatively small differences in precipitation: during the six-month period from June 01 to November 30, 2003 (the non-ENSO base year), total average rainfall was 1,379 mm in Palolo and 1,134 mm in Kulawi, which in the severe El Niño scenario is reduced to 45% and 50% of this level, respectively. However, there are marked differences in hydrologic characteristics, i.e. the availability of irrigation water: while total estimated discharge during the base period was approximately 2,900 mm in Palolo, it amounted to 6,100 mm in the much larger Kulawi catchment; the gap becomes even more pronounced in the severe El Niño scenario, when total discharge is reduced to a mere 800 mm (28% of the 'normal' level) in Palolo in contrast to 3,400 mm (56%) in Kulawi.

3.2 Modelling the impact of ENSO on crop yields

To quantify the impact of different climatic and crop management scenarios on the yields of the major crops in the area, irrigated rice, maize, and cocoa, Cobb-Douglas production functions of the following general form are estimated:

$$\ln Y_{it} = \beta_0 + \sum_{m=1}^{n} \beta_{0m} D_{mit} + \sum_{k=1}^{l} \beta_k \ln(X_{kit}) + \varepsilon_{it} \qquad (1)$$

where

ln Y = Natural logarithm (ln) of the output

i = Household index (i = 1,…,N; N = 113, 97, and 34 for rice, cocoa, and maize, respectively)

t = Time index (t = 1,…,T_{max}; T_{max} = 4 [cropping seasons] for rice and maize, T_{max} = 2 [years] for cocoa)

β = Vector of parameters to be estimated

D_m = Vector of dummy variables

ln X_k = ln of the input vector, including climate-related variables

ε = N (0, σ_ε) distributed random error term

The dependent variables are the natural logarithms of the reported yields of husked rice, dried maize seeds, and dried cocoa seeds. Apart from variables measuring the input of land, labour, and capital, the production functions contain climatic and hydrologic variables as additional input factors, again as natural logarithms. Several dummy variables account for differences in important qualitative factors. The definition of all variables and their summary statistics are provided in Table 3 (section 5).

In the production functions of maize and cocoa we include variables measuring the amount of rainfall received during the cropping season/year in a given village; the squared term of this variable allows the partial production elasticity of rainfall to be non-constant and output to decline at very high precipitation levels. In the case of irrigated rice we include a variable measuring rainfall plus the calculated total discharge in the corresponding sub-catchment during the cropping season, the latter being a proxy of the amount of irrigation water available (see section 3.1). In some cases no cash inputs were applied. These 'zero-observations' may

lead to biased parameter estimates of the respective explanatory variables; to correct this, we follow the procedure proposed by Battese (1997) and include dummy variables that take on the value of one in the case of a 'zero-observation' of the corresponding explanatory variable, and the value of zero otherwise.

3.3 Simulating cropping strategy decisions using linear programming

To include the effects of changing resource allocation into the analysis of the effects of climate variation at the household level, we construct an LP-model. Its aim is to simulate farmers' crop management decisions under reduced yield expectations due to predicted adverse weather patterns. An LP-model determines the levels of activity variables (such as cultivating different crops, buying inputs, or selling outputs) under a set of constraints (such as resource availability) in order to optimise the level of an objective variable (Hazell and Norton 1986). We assume that the objective driving farming decisions is the maximisation of farm income, but we account for competing household objectives, such as leisure and rice production for home consumption, through the formulation of respective constraints. Through the introduction of time-steps, seasonal effects are also considered. Rather than seeking to identify improved farm management strategies under the current conditions, the objective of the model is to reveal the consequences of changes in the production environment. The effects of climate variation are simulated based on the ENSO scenarios described in section 3.1. In these scenarios, yield expectations of the major crops are reduced according to the predicted rainfall patterns and the estimated production functions, thus altering the relative attractiveness of the major crops.

3.4 Introducing risk: Stochastic simulation of crop production and its integration into the linear programming model

An LP-model is a deterministic simulation model that produces "optimal" solutions based on the assumption that economic agents have complete control over the production process. In our case, the average yield levels defined for rice, cocoa and maize are based on the deterministic component of equation (1), i.e. the random error term ε is ignored. However, in contrast to industrial processes, agricultural production is subject to considerable yield fluctuations caused by variations in the incidence and severity of pests and diseases, micro-climatic and soil conditions, as well as management characteristics (Anderson *et al.* 1977).

In equation (1) these stochastic yield components, along with measurement errors[5], are contained in ε. Hence, in order to estimate the risk involved in the production process, we extend both the results of the production functions and of the household model by combining the average yield estimates with the stochastic simulation of the error term. The objective of

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[5] In our analysis the measurement error is not considered as it is assumed to be limited: farmers are well aware of their crop yields as they pay for rice husking per unit harvested while maize and cocoa are grown as cash crops. Moreover, by collecting plot-level data and breaking down labour input questions by specific field operations, measurement errors of input variables are minimised.

the latter is to generate random numbers that match the true residuals in terms of functional form, mean, and standard deviation, whereby the validity of the simulation outcome can be tested (Law and Kelton 2000).

Using this approach, we derive two types of crop output estimates for a given level of inputs: (1) Point estimates of average yields that are based on the regression analysis only; these lead to unambiguous and, hence, easily interpretable optimal solutions of the linear programming model (section 5.3). And, (2), probability distributions of yield levels, based on the combination of regression analysis and stochastic simulation. By reflecting yield variations that are beyond the control of the farmer they allow for a more comprehensive evaluation of farm management strategies (section 5.2).

By introducing random yield factors derived from the probability distribution of ε in equation (1) into the crop output equations for rice, cocoa and maize, the stochastic component of output estimates is incorporated into the LP-model. Iterative model runs with changing random yield factors produce a set of model outcomes, from which probability distributions are derived. The downside risk of failing to achieve a specified minimum level of income is a particularly insightful output of this methodology (section 5.4).

4   The household model applied, and data used

Model structure

The LP-model covers 12 half-monthly time-steps from June to November, the period during which ENSO-induced droughts are felt most acutely. In each of these balances are calculated for labour, cash and outputs. The model objective is to maximise the level of cash in the last period. The determination of cropping patterns takes three types of crop land into account: Irrigated and non-irrigated land for annual crops (rice can only be grown on irrigated land, all other crops can be grown on all annual crop land) as well as cocoa plantations (cocoa can only be grown on cocoa plantations). Household labour capacity and household food requirements also critically determine model outcomes. All three major crops can be grown at three levels of production intensity (average observed level of input use, 75% of observed level, 125% of observed level). The respective output levels are calculated via the estimated production functions. There is no statistically significant evidence that the reduced supply of either rice or cocoa lead to an increase in farm gate prices mitigating the impact of reduced yields on agricultural income (Keil 2004: 77); hence, constant prices are assumed. Rice and maize can be planted during two specific time-steps (first half of June or first half of July).

Two crops more adapted to dry conditions, soybeans and groundnuts, are also included in the model to test their attractiveness under the defined ENSO scenarios. With water requirements of around 500 mm during the 4-6 month vegetation period (Rehm and Espig 1991: 95; 99), they are assumed to produce full yields also under El Niño conditions.

In addition to allocating crops to the available land, the main activity variables are the allocation of family labour, the hiring of labour, taking credit, and the sale and purchase[6] of outputs.

In the case of rice we correct for a limitation in the estimation of the production function (see section 5.1) by introducing a minimum water availability threshold as an additional production constraint to adequately account for its water requirements. According to the International Rice Research Institute, 10 mm of water per day are required to irrigate a rice crop, amounting to 1,000 mm for a crop that matures in 100 days; longer maturing varieties require proportionately more water (IRRI 2005). Thus, in our model, rice can only be grown if total water supply from rainfall and irrigation exceeds 1,000 mm during the cropping season. This threshold takes into account that growing rice is still feasible at somewhat suboptimal levels of water supply, since the average vegetation period of rice is 120 days in the research area, corresponding to a total water demand of 1,200 mm.

Data used

In early 2005 the socioeconomic data were collected in a stratified random sample of 228 farm households. To capture the variation in local climatic conditions, eight out of the 53 villages located in the Palu River watershed were randomly selected using elevation above sea level as stratification criterion. In a second step, farm households were randomly selected in these villages using locally available lists of households as sampling frame, which were based on the most recent village census. Based on farmer recall, production data were collected for the three most important crops, rice, maize, and cocoa, covering the years 2003 and 2004, i.e., two years of cocoa production and up to four cropping seasons of rice and maize. The total number of observations is 408, 190, and 79 for rice, cocoa, and maize production, respectively. For the same time period measured rainfall data are derived from weather stations set up in each research village, and discharge data from hydrologic instruments installed in key locations of the watershed. Output levels and input requirements of the two alternative crops considered, soybeans and groundnuts, are based on secondary data from the local agricultural extension service.

Household classification

To capture differences in resource endowment and farming systems, the household-level data are classified into typical farm household classes. This is achieved by performing cluster analysis separately on the 96 survey households from the low-lying sub-district of Sigi Biromaru and on the 132 survey households from the higher elevation areas of Palolo and Kulawi (cf. section 2). Clustering variables are related to resource endowment, cropping characteristics, and drought risk exposure (Table 2). Outliers are excluded according to a 5% threshold of the density function (Silverman 1986). Hierarchic clustering determines the optimal number of classes per sub-region: four classes in the low-lying sub-region and five

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[6] Only rice is considered with regard to household food requirements.

classes in the higher region. Cluster composition is refined through a subsequent non-hierarchic cluster analysis. The resulting distribution of households among the clusters as well as the within-cluster means of the clustering variables are presented in Table 2.

Table 2. Results of the cluster analysis, indicating mean values of the clustering variables for nine household classes d1 to u5

	Lowland (d = down)				Upland (u = up)				
Cluster notation	**d1**	**d2**	**d3**	**d4**	**u1**	**u2**	**u3**	**u4**	**u5**
(N)	(16)	(37)	(23)	(15)	(19)	(27)	(25)	(20)	(34)
Drought impact index[a]	3.7	3.5	3.7	4.1	2.4	3.6	3.2	2.6	1.8
Cropped area [ares]	119.1	89.9	84.1	319.7	176.6	121.7	150.0	492.8	181.9
HH labour capacity (>=10 years of age) [AE]	3.5	2.7	2.9	3.9	5.0	2.3	3.3	4.2	3.3
Irrigated rice area per cropped area [%]	27	90	12	42	27	15	67	23	3
Cocoa area per cropped area [%]	52	2	2	26	38	37	17	22	80
Poverty Index[b]	-0.38	-0.17	-0.25	1.21	0.53	-0.93	-0.46	-0.03	0.66
Total off-farm income ['000 IDR]	991.6	970.9	963.3	1751.1	5405.4	971.9	773.5	553.2	1124.7

[a] Based on the perceived impact of the most severe drought experienced by the household, on a scale from 0 (no impact on the welfare of the household) to 5 (very serious impact) (Keil 2004: 73).

[b] Based on asset- and consumption-related indicators. The Poverty Index is the first factor extracted by Principal Component Analysis. It has a mean of 0 and a standard deviation of 1 (Keil 2004: 154-155).

To focus on the differences in household reactions to climate variation, only the four most disparate household classes are considered in the subsequent analysis, which are classes d2 and d4 in the low-lying area and classes u1 and u5 in the upland area. Table 2 shows that households in class d2 are characterised by small farm size and an extreme emphasis on rice production (0.9 ha, 90% of which is planted to rice), households in class d4 crop larger areas and are less rice-based (3.2 ha, 42% rice), farms in class u1 are medium-sized with mixed cropping patterns and some emphasis on cocoa (1.8 ha, 38% cocoa), while class u5 is similarly sized but highly specialised on cocoa (1.8 ha, 80% cocoa). To account for differences in climatic and hydrologic conditions between Palolo and Kulawi (cf. Table 1), class u1 is duplicated with one version (denoted u1) being linked to the production functions and climate scenarios defined for Palolo and the other (denoted u6) being linked to Kulawi.

5   Results

5.1   Modelling the impact of ENSO on crop yields

The definitions and summary statistics of the variables included in the production functions for irrigated rice, maize, and cocoa are listed in Table 3. All data are given at the household level.

Table 3. Variables used in the estimation of production functions for irrigated rice, maize, and cocoa in Central Sulawesi, and their summary statistics

Variable	Rice Mean	Rice Std. Dev.	Maize Mean	Maize Std. Dev.	Cocoa Mean	Cocoa Std. Dev.
Dependent variable[a]:						
Output	**978.42**	825.09	**907.11**	1010.80	**904.04**	999.03
Continuous independent variables[a]:						
Land	**67.26**	46.60	**53.58**	30.38	**106.04**	94.46
Labour	-		**118.22**	88.00	**460.46**	420.53
Seeds	**86.51**	58.90	-		-	
Fertilizer	**109335.89**	130951.43	**74035.44**	117346.16	-	
Herbicides	**33718.72**	46561.83	-		-	
Materials	-		-		**360146.76**	874941.76
Rain	-		**469.87**	208.47	**1790.46**	635.26
Water	**2893.15**	1605.25	-		-	
Temperature	-		-		**24.73**	1.58
Age	-		-		**8.94**	3.52
Dichotomous independent variables:						
Pests/diseases	**0.19**	0.39	**0.09**	0.29	**0.38**	0.49
HYV	**0.07**	0.25	-		-	
Several plots	-		-		**0.35**	0.48
No fertilizer	**0.12**	0.33	**0.49**	0.50	-	
No herbicides	**0.20**	0.40	-		-	
No materials	-		-		**0.40**	0.49

[a] For ease of interpretation, summary statistics are given for the unlogged variables.

The definition of variables is as follows:

Output = Logged total crop output (kg of husked rice; kg of dried maize seeds; kg of dried cocoa seeds).

Land = Logged total input of land (ares).

Labour = Logged total input of labour (manhours).

Seeds = Logged total input of rice seed (litres).

Fertilizer/Herbicides/Materials = Logged total input of fertilizer/herbicides/all materials (IDR); IDR = Indonesian Rupiah; 1 US$ = 8,900 IDR (February 2003).

Rain = Logged total amount of rainfall (mm) during the cropping season (maize)/during the year (cocoa).

Water = Logged total amount of rainfall and available irrigation water during the cropping season (mm).

Temperature = Logged mean annual temperature (°C).

Age = Logged weighted mean age of the cocoa plantation (years).

Pests/diseases = Dummy, = 1 if yield was drastically reduced by pests/diseases, 0 otherwise.

HYV = Dummy, = 1 if high-yielding variety was used, 0 otherwise.

Several plots = Dummy, = 1 if household cultivates several plots [which often differ significantly in terms of location and, hence, micro-climatic and soil characteristics], 0 otherwise.

No fertilizer/No herbicides/No materials = Zero-observation dummies, = 1 if Fertilizer/Herbicides/Materials is zero, 0 otherwise.

Table 4 presents the regression results; the signs of all regression coefficients, notably those of the rainfall-related explanatory variables *Rain*, *Rain squared*, and *Water*, are as expected, and the coefficients are statistically highly significant.

Table 4. Ordinary Least Squares (OLS) estimates of the parameters in the Cobb-Douglas production functions for rice, maize, and cocoa production in Central Sulawesi

Variable	Rice Coefficient	Rice t-value	Maize Coefficient	Maize t-value	Cocoa Coefficient	Cocoa t-value
Constant	- 0.161	- 0.359	-18.672	- 2.150*	- 60.808	- 3.688***
Land	0.465	8.249***	0.448	3.529**	0.757	9.618***
Labour	-		0.213	2.107*	0.265	4.927***
Seeds	0.301	4.782***	-		-	
Fertilizer	0.148	4.958***	0.357	2.937**	-	
Herbicides	0.110	3.796***	-		-	
Materials	-		-		0.106	2.035*
Rain	-		6.008	2.129*	13.430	3.330**
Rain squared	-		- 0.480	- 2.066*	- 0.867	- 3.191**
Water	0.119	3.606***	-		-	
Temperature	-		-		2.646	2.085*
Age	-		-		0.399	2.989**
Pests/diseases	- 0.377	- 8.008***	- 0.954	- 4.895***	- 0.640	- 6.383***
HYV	0.201	2.682**	-		-	
Several plots	-		-		0.297	2.520*
No fertilizer	1.255	3.829***	3.285	2.388*	-	
No herbicides	0.955	3.294**	-		-	
No materials	-		-		0.946	1.502

	Rice	Maize	Cocoa
	N = 408	N = 79	N = 190
	F = 165.966***	F = 39.747***	F = 72.949***
	$R^2 = 0.790$	$R^2 = 0.797$	$R^2 = 0.803$
	Adjusted $R^2 = 0.785$	Adjusted $R^2 = 0.777$	Adjusted $R^2 = 0.792$

*(**)[***] Statistically significant at the 5% (1%) [0.1%] level of error probability.

The impact of rainfall on rainfed crops

Based on the regression coefficients of the variables *Rain*, *Rain squared*, and *Water* crop yields can be calculated for different rainfall scenarios. Figure 2 illustrates the relationship between rainfall and yield for the rainfed crops maize and cocoa, calculated at the means of the other production factors. In accordance with plant physiology, yields decline beyond an optimum level of rainfall.
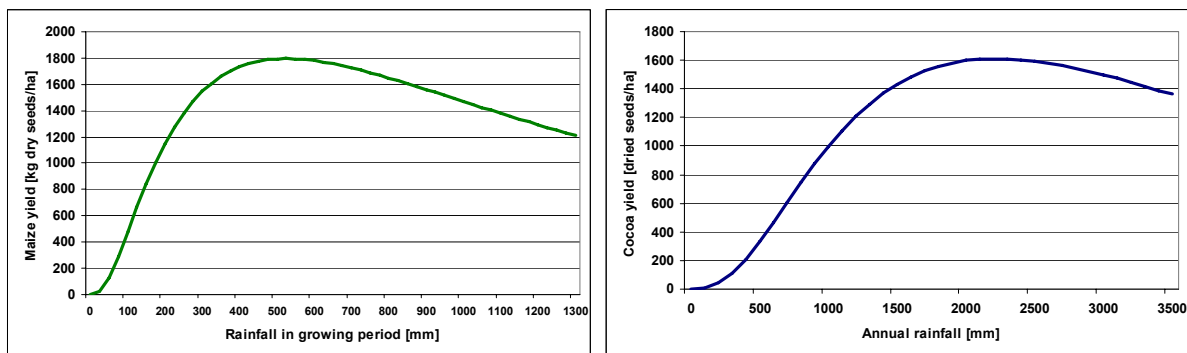

Figure 2. The relationship between rainfall and yield for maize (left) and cocoa production (right) in Central Sulawesi, Indonesia, based on empirically estimated production functions.

The impact of water availability on irrigated rice

The regression coefficient of the variable *Water* in the production function for rice is positive and statistically highly significant (Table 4). However, at 0.119 the size of the coefficient, representing the partial production elasticity in the Cobb-Douglas-type production function, is quite small. It indicates that rice yields would decline by only 1.2% under a 10% reduction in water supply. The likely underestimation of the water-related regression coefficient led to the introduction of an absolute water availability threshold into the LP-model, as elaborated in section 4.

5.2   Accounting for risk: combining regression analysis with stochastic simulation

Figure 2 is based on the share of variance in output explained by the regression analysis, which is approximately 80% (see R^2-values in Table 4). The remaining 20% of variability are due to factors beyond the control of the farmer or unobserved management characteristics (see section 3.4). Stochastic simulation is used to model this unexplained yield component ε in equation (1). As a first step, the distribution of ε is tested for normality: the null-hypothesis of a normal distribution is accepted for all three regression models (Cramér-von-Mises test, 95% confidence level). Hence, the normal distribution is used for the simulation of stochastic yields as follows: the mean is equal to the deterministic component of equation (1), i.e., the mean of the simulated residuals is zero; the standard deviation is equal to that of the true residuals. Second, in order to avoid unrealistically high simulated yields, the normal distribution is truncated by defining maximum yield levels of 5,000 kg ha^{-1} for rice, 6,000 kg ha^{-1} for maize, and 5,000 kg ha^{-1} for cocoa; according to the local agricultural extension service, these are the maximum yields that can possibly be attained for these crops in the research area. Finally, the means and variances of the simulated residuals (500 iterations) are compared to those of the true residuals: in all three cases, the independent-samples t-test fails to reject the null-hypothesis of equal means, and the F-test fails to reject the null-hypothesis of equal variances (95% confidence level). We thus conclude that our simulation of ε is adequate for all three crops.

In our estimation of the impact of ENSO-related drought on crop yields we now combine the results of the regression analysis with the simulation of stochastic yield fluctuations. As an example, Figure 3 displays the drought impact on the yield of cocoa, based on the sub-district-specific rainfall reduction during 'average El Niño' and 'severe El Niño' events (see Table 1). The mean yields in the three scenarios are those attained with a cumulative probability of 50%; for example, in Sigi Biromaru (bottom panel), mean cocoa output during the six-month period from June 01 to November 30 declines from 530 kg ha^{-1} of dried beans under 'normal' conditions to 241 and 114 kg during an average and a severe El Niño event, respectively. To highlight the differences in the local impact of El Niño, the figure indicates the probabilities of attaining an output level of 250 and 500 kg in the three sub-districts: while in Kulawi the probability of failing to attain an output of 250 kg increases only slightly from 13 to 19% during an average El Niño relative to a 'normal' year, it increases substantially

from 14 to 35% in Palolo and climbs dramatically from 16 to 54% in the low-lying sub-district of Sigi Biromaru. During a severe El Niño event the respective probabilities increase to 39, 41, and 86%.
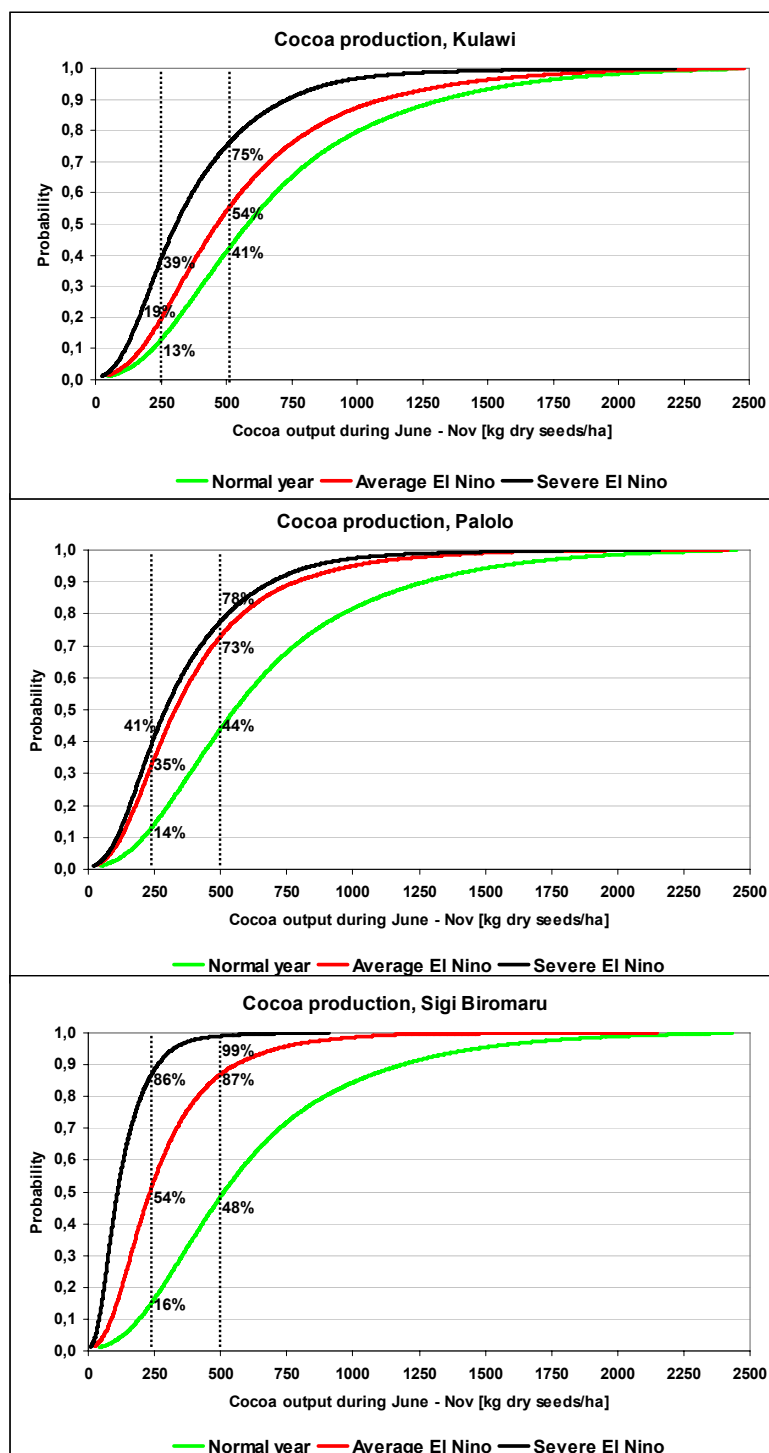

Figure 3. Cumulative distribution functions of cocoa yields in Central Sulawesi during non-ENSO, average El Niño, and severe El Niño years, differentiated by sub-district.

5.3 Deterministic model output: optimal resource allocation under different climate scenarios

Figure 4 displays the LP-model solution with regard to the allocation of land to different cropping activities and production intensities for a non-ENSO and a severe El Niño season for the lowland household classes d2 and d4: in the non-ENSO scenario, d2 allocates 82% of the available cropping area to irrigated rice, 15% to maize, and 3% to cocoa. To mitigate labour bottlenecks, 56% of the rice area is planted early, i.e., in June, and the remaining 44% one month later. Furthermore, a 'medium' input intensity is adopted for the early rice, whereas the 'high' intensity level is applied to most of the late rice[7]. Household class d4 allocates 41% of the cropping area to rice, 31% to maize, and 28% to cocoa.
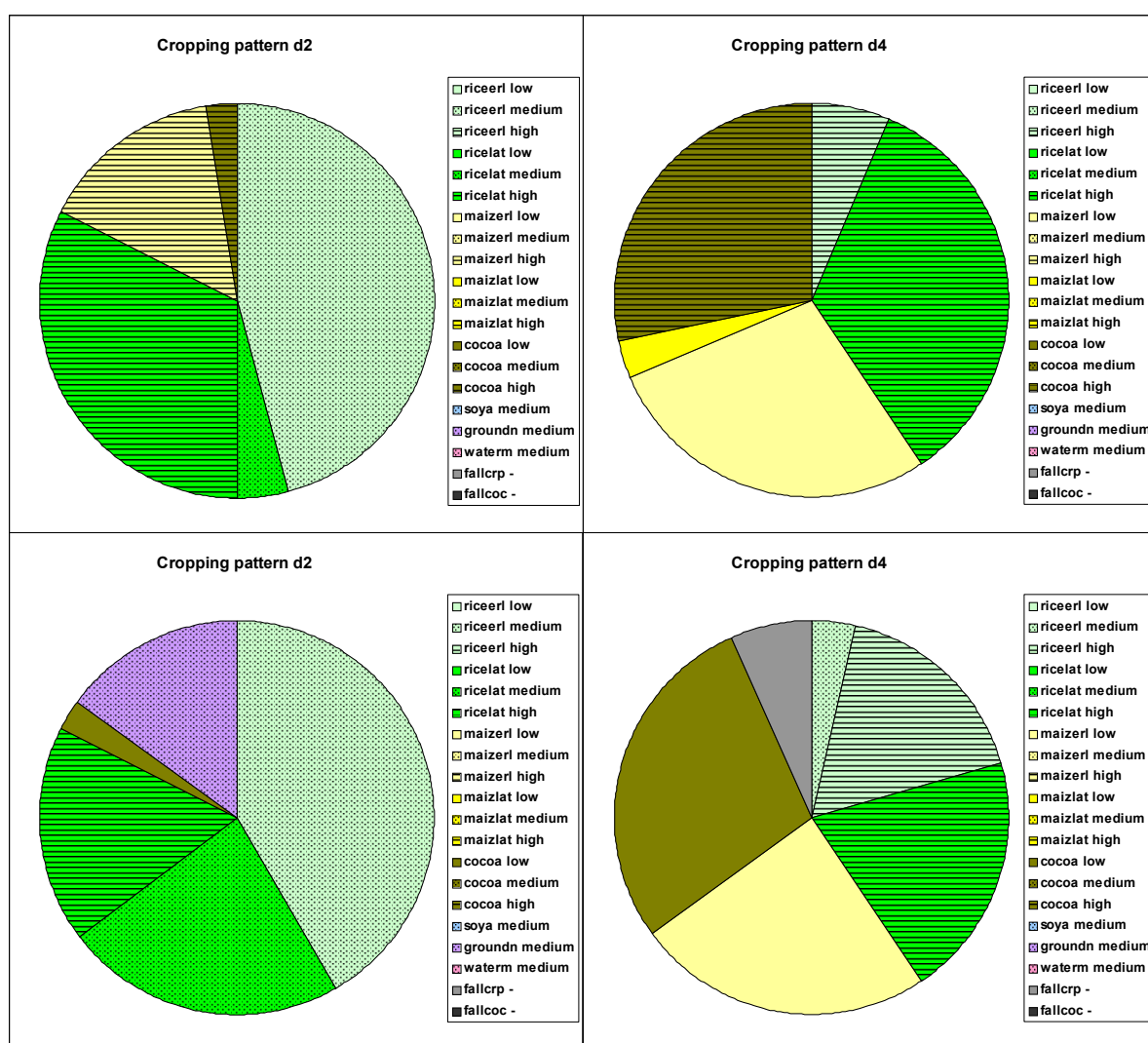

Figure 4. Optimal cropping strategies in Central Sulawesi during a non-ENSO year (top) and a severe El Niño year (bottom) for farm household classes d2 (left) and d4 (right).

Part of the rice and maize is planted in June and part in July, input intensities are high for rice and cocoa and low for maize. In the case of a severe El Niño, d2 reduces the input intensity from 'high' to 'medium' on part of its late rice and its cocoa and replaces maize by

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[7] See section 4 for the definition of potential cropping activities, including planting dates and intensity levels.

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groundnuts, a more drought-tolerant crop. Household class d4 also reduces input intensities in cocoa production and some share of rice and adjusts planting dates for rice; part of the land that is normally planted to maize remains fallow. Hence, the model recommends considerable adjustments to intensity levels and cropping patterns for both household classes in the severe El Niño scenario as compared to the ,normal' climate scenario.

Based on the same scenarios, Figure 5 depicts the model solutions for the upland household classes u1 and u6, which feature identical socio-economic characteristics but differ in terms of location: u1-households reside in the Palolo valley and u6-households in the Kulawi valley. The more favourable hydrologic conditions in Kulawi (cf. Table 1) have important implications: in the non-ENSO scenario both household classes dedicate 25% of their cropping area to rice and 22% to maize while 53% are occupied by cocoa[8].
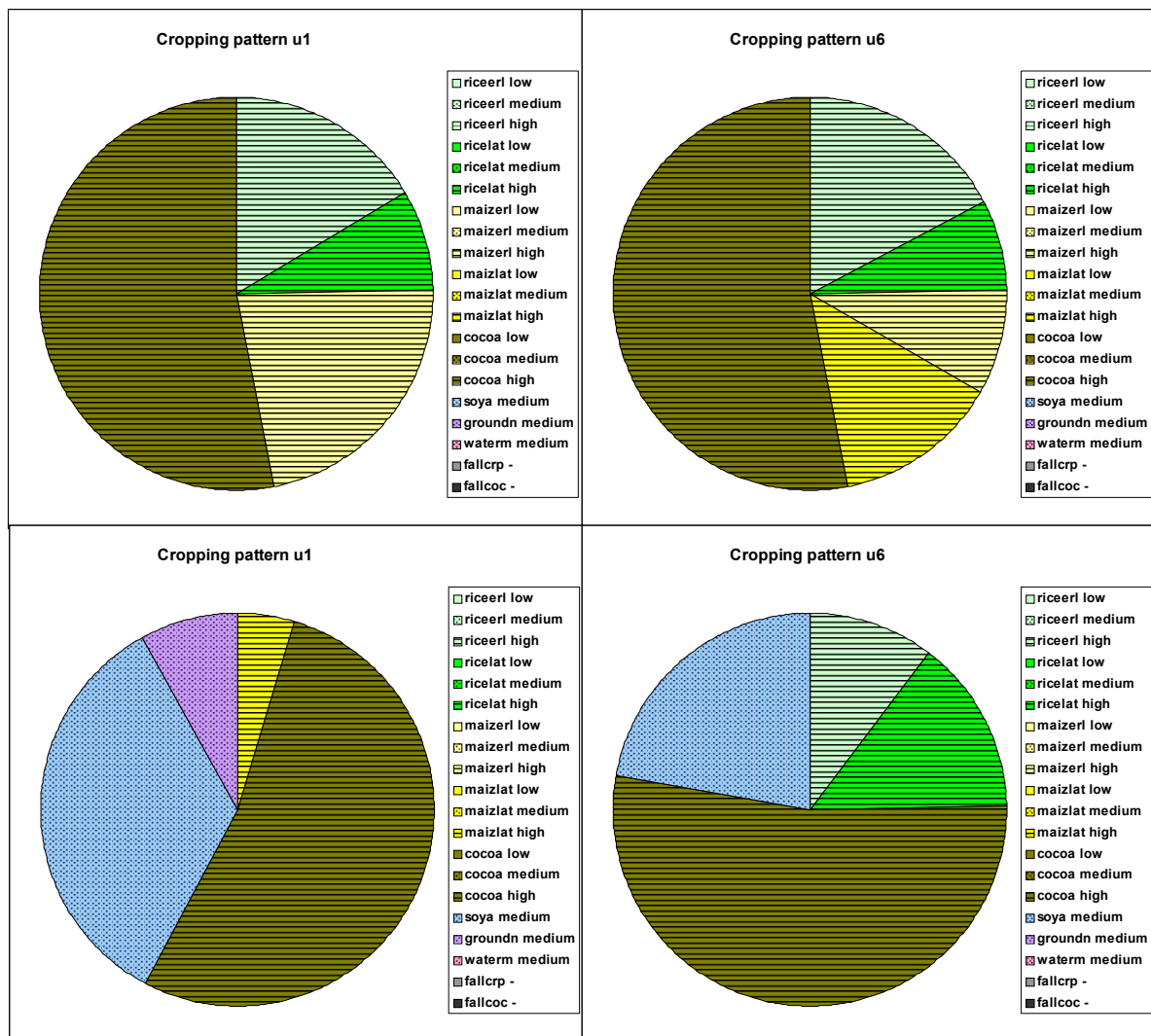

Figure 5. Optimal cropping strategies in Central Sulawesi during a non-ENSO year (top) and a severe El Niño year (bottom) for farm household classes u1 (left) and u6 (right).

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[8] The discrepancy in planting dates for the maize crop is caused by small differences in the relative yields of the three crops due to the different climatic and hydrologic conditions, leading to slight deviations in labour allocation.

During the severe ENSO scenario u6 can continue to grow rice while replacing maize by the more drought-tolerant soybeans. In contrast, it is not possible for u1-households to continue growing rice since the specified minimum water requirement of 1,000 mm during the 120-day growing period is not met (cf. section 4). For this class the model strategy is to allocate 34% of the available cropping area to soybeans, 8% to groundnuts, and continue maize cultivation on 5%. It is important to note that the total water supply in the Palolo valley during the first 100 days after transplanting, during which rice is particularly sensitive to water stress (IRRI 2005), is estimated to be a mere 410 mm for the average-ENSO and 390 mm for the severe-ENSO scenario. Therefore, even under the assumption of considerably lower minimum water requirements rice cultivation is not a viable option.

For all five household classes considered in the analysis, Figure 6 visualizes the susceptibility towards drought-induced income reductions. To make income levels comparable and more easily interpretable, the total agricultural income generated in the six-month simulation period is converted into USD per Adult Equivalent (AE) per day; an AE is based on caloric requirements, differentiated by gender and age (WHO/FAO 1973).
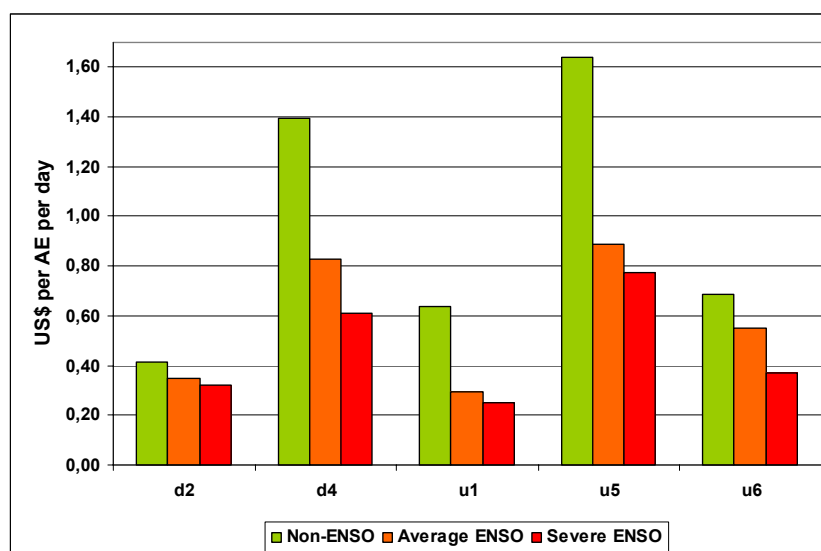

Figure 6. Comparison of agricultural income levels in USD per Adult Equivalent* per day of all farm household classes modelled during the period June 01 to Nov. 30 for a non-ENSO, an average El Niño, and a severe El Niño year.

* Adult Equivalents are based on caloric requirements, differentiated by gender and age (WHO/FAO, 1973)

While the daily agricultural income of d2 is the lowest at 0.41 USD/AE during the non-ENSO scenario, it is also the most stable with a reduction to 83 and 78% of the 'normal' level in the average and the severe El Niño scenarios, respectively. At 1.64 USD/AE the daily agricultural income of the cocoa-based household class u5 is the highest, followed by the large, diversified farms in class d4 (1.40 USD/AE); however, both classes experience considerable income reductions in the two ENSO scenarios, at 60 and 44% of the 'normal' level for d4, and 54 and 47% for u5, respectively. While daily incomes of household classes u1 (Palolo)

and u6 (Kulawi) are similar under non-ENSO conditions at 0.64 and 0.69 USD/AE, respectively, Palolo-households suffer greater income losses during El Niño, mainly because the disadvantageous hydrologic conditions impede a successful cultivation of rice: their income is drastically reduced to 46 and 39% in the two ENSO scenarios, as opposed to a much more moderate reduction to 80 and 56% in the case of their Kulawi counterparts.

5.4 Accounting for risk: introducing stochastic simulation to the household model

The cumulative distributions of cash and credit levels displayed in Figure 7 are based on 100 iterative runs of the LP-model, whereby crop yields randomly vary according to the simulated distribution of the residuals in the production functions (cf. Figure 3 for the example of cocoa). The graph depicts the cumulative distribution functions for the five considered household classes under the non-ENSO and the severe El Niño scenarios. Positive values on the x-axis correspond to cash-levels obtained by the end of the six-month simulation period, while negative values reflect total credit requirements during the same period.

In addition to the deterministic results displayed in Figure 6, we can now derive information on the levels of risk involved in the cropping systems practised: for example, the distribution functions of household classes d4 and u5 cross each other under both climate scenarios; this means that the cropping strategy of u5-households, which devote 80% of their cropping area to cocoa and are therefore highly specialized (cf. Table 2), involves a higher level of risk than the more diversified crop portfolio of d4-households. By disregarding the lower and upper 10%-tails of the distribution functions, one can state that with a probability of 80% d4-incomes will fall within a range from 4.5 to 14.0 million IDR, whereas u5-incomes will range from 3.3 to 15.8 million IDR. With a probability of roughly 70% in the non-ENSO and 50% in the ENSO scenario, d4 will achieve a higher level of income than u5.

Furthermore, the graph shows that with certainty households in class d2 require credit for financing agricultural inputs in both climate scenarios. Class d4 can do without a loan with a probability of approximately 75% during 'normal' years, but this probability declines to less than 10% in the severe-ENSO scenario; moreover, in the drought scenario, d4 needs to borrow a larger sum than d2 with a probability of around 80% (the two functions intersect at a probability level of 0.20). Also for classes u1 and u6 the risk of having to take a loan significantly increases from around 5% under 'normal' to approximately 30% under drought conditions, but the amount that has to be borrowed is relatively small. Only the cocoa-based household class u5 never relies on credit to finance agricultural inputs because of a continuous flow of revenue from fortnightly sales of dried cocoa beans.

The modelling results can be used to derive the probabilities of different household classes to fall below a specified income level: for illustrative purposes, the vertical lines in Figure 7 mark an agricultural income level of 1 USD per day per AE[9]. Since household classes differ

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[9] Note that this level is not identical with the international poverty line used by the World Bank and other international institutions since it is not adjusted for purchasing power parity and does not consider off-farm income.

in their demographic composition (except u1 and u6), different total cash levels correspond to this threshold. The graph shows that d4- and u5-households exceed the threshold with a probability of roughly 75% during 'normal' years, household classes u1 and u6 have a chance of 15-20% of doing so, and for d2-households the chance is negligible. However, during El Niño, all household classes are very likely to fall beneath the 1 USD threshold, whereby, at 90%, the probability is higher for the mixed d4-households than for the cocoa-based u5-households (70%).
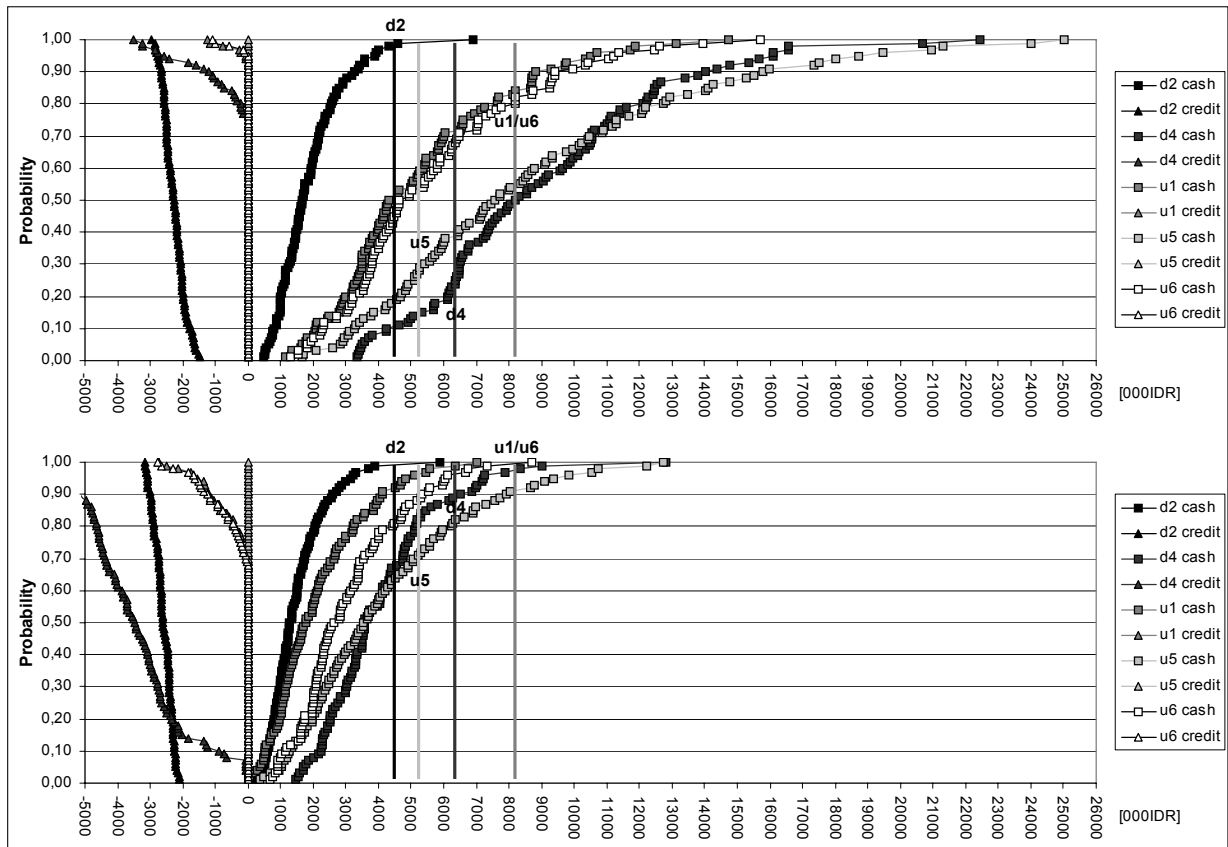

Figure 7. Cumulative distribution functions of the cash levels attained and total credit requirements over the period June 01 to Nov. 30 for all modelled household classes during a non-ENSO year (top) and a severe El Niño year (bottom), accounting for stochastic yield fluctuations. The vertical lines correspond to a 1 USD per Adult Equivalent per day income threshold for the different household classes.

Note: The graphs are based on 100 iterative runs of the Linear Programming Model in combination with stochastic simulation of the output variability not explained by the production functions of rice, maize, and cocoa.

6   Discussion and conclusions

Modelling the impact of ENSO on crop yields

Our approach of using regression analysis to estimate the relationship between rainfall and crop yields proved successful in the case of the rainfed crops maize and cocoa. The empirically estimated yield maximum at 525 mm of rainfall per growing season in the case of maize and 2,200 mm per year in the case of cocoa is consistent with values found in the literature (Franke 1994a: 76; 1994b: 22). In the case of rice, regression analysis produced a very small coefficient of the *Water* variable (cf. Table 4), implying an underestimation of the

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impact of water supply on rice yields. This limitation of our approach is likely to be caused by the fact that farmers will reduce the area planted to rice under drought conditions and attempt to adequately irrigate the remaining rice plots; thus, the effect of drought is in terms of area harvested rather than yield (Falcon *et al.* 2004). Having planted too much rice at the drought onset is likely to entail a complete crop failure in one or several paddy fields that cannot be sufficiently irrigated. However, a complete crop failure cannot be captured by the regression analysis because cases of zero-yields have to be excluded in order to avoid biased estimates. This leads to a limited variability in the data set and, therefore, to an underestimation of the regression coefficient of the water-related variable. Cases in which farmers chose not to plant rice due to a drought situation are, naturally, also not captured by the regression model.

Identifying optimal crop management strategies

In general, an optimal adaptation of cropping activities to drought conditions comprises two elements: first, a reduced production intensity of crops that are usually grown; this is due to the drought-induced depression of crop yields, leading to reduced marginal returns per input unit applied. Thus, in the case of drought, a reduced input intensity will be closer to the economic optimum. And, second, if the yields of the annual crops rice and maize fall below a certain threshold level, or if the specified minimum water supply of 1,000 mm for a rice crop cannot be met, these crops should be replaced by more drought-tolerant ones. While the simulations do reflect these general adaptation strategies, the main value of the model lies in demonstrating how optimised adaptation strategies differ between individual household classes, depending on their resource endowment and the micro-climatic and hydrologic characteristics of the environment they are located in. For example, different strategies apply to the two lowland household classes d2 and d4 because of differences in their crop portfolios as well as their endowment with land, labour, and capital. Different strategies also apply to the two upland household classes u1 and u6 due to differences in the climatic and hydrologic conditions of their locations; it is worth noting that these differences could only be identified through the inclusion of hydrologic modelling results, thus illustrating the added value of an interdisciplinary modelling approach.

Modelling the impact of drought on agricultural incomes

There is empirical evidence that drought-induced declines in crop yields are not significantly mitigated by local price effects (Keil 2004). In the case of rice the lack of price effects may be explained by the heterogeneity of both climatic conditions and irrigation facilities within the research area, allowing localized drastic reductions in rice supply to be relatively easily compensated; in the case of the primary cash crop cocoa prices are, of course, largely determined by world market conditions. The LP-model shows that, in general, all drought-affected households suffer considerable income losses even if they adapt their resource allocation in an optimal way. The magnitude of the simulated El Niño-related income losses is in line with the findings of Salafsky (1994), Harger (1995), and Amien et al. (1996). However, we extend these findings by illustrating the large difference between household

types in terms of drought impact: the poorest, rice-based class, d2, is the least susceptible to income losses; this class is shielded from drought effects by a reliable irrigation system that is fed by a large watershed. On the other hand, relatively wealthy cocoa-based farmers (u5) are highly susceptible to drought, suffering an income loss of around 50% during the simulation period. The example of household classes u1 and u6 highlights the monetary consequences of climatic and hydrologic differences between locations: the erratic supply with irrigation water in a small sub-watershed makes households in class u1 particularly prone to drought-induced income depressions.

Accounting for risk through stochastic simulation

The stochastic results complement and extend the deterministic output. The range of potential outcomes corresponds to the level of risk involved in a given crop portfolio and, as the results demonstrate, there are marked differences in the levels of production risk that individual farm household classes face: for example, the level of risk is relatively low in cases where agricultural production is based on rice in a technical irrigation system with a relatively reliable water supply (d2) and relatively high in cases of cocoa-based farming systems (u5).

The modelling results can be used as a measure of vulnerability of the different household classes, defined as their probability of falling below a specified income level (Morduch 1994): even under non-drought conditions, only households in classes d4 and u5 are capable of generating average agricultural incomes greater than 1 USD per day per AE. During El Niño, all household classes are very likely to fall beneath the 1 USD threshold, whereby the mixed d4-households prove more vulnerable than the cocoa-based u5-households; hence, while u5-households are susceptible towards drought-induced income losses and face a relatively high level of production risk, they are the least vulnerable household class, i.e., they are the least likely to (temporarily) fall below a specified poverty line. It is important to note that the amount of off-farm income generated in the research area is of minor importance; moreover, sources of off-farm income are mainly agricultural wage labour or locally marketed goods and services (Keil 2004: 134), both of which are likely to be adversely affected by drought due to reduced demand (Fafchamps *et al.* 1998).

In summary, we draw the following conclusions from our modelling results: Although our illustrative 1 USD threshold does not reflect the international poverty line, we can conclude that, in general, El Niño-related drought drastically increases the probability of failing to meet minimum household requirements. This is in line with the empirical findings of Keil (2004: 93; Keil *et al.* forthc.) who reports that 62% of a random sample of farm households had to reduce expenditures for basic necessities as a consequence of severe drought periods, whereby off-farm income is found to have no significant effect on the households' ability to smooth consumption. However, there are marked differences in the severity of impact between different types of farm households, depending on their location, farming system, and resource endowment. In general, adaptation strategies to mitigate the adverse impact on agricultural

incomes should encompass a reduction of production intensities and, in the case of serious drought conditions, a replacement of the predominant annual crops rice and maize by more drought tolerant ones, e.g., soybeans or groundnuts. However, a crucial prerequisite to the recommendation of a particular alternative crop is a thorough assessment of the agronomic and marketing potential under the specific frame conditions of a given area. By highlighting the diversity among farm households and its implications on El Niño impacts, the modelling results demonstrate that a one-fits-all type of policy strategy is not appropriate with regard to climate impact mitigation in an area characterised by a high degree of agro-ecological and socio-economic diversity: policy measures need to be carefully tailored to the farming systems and environmental frame conditions found in a given area if they are to be both effective and economically efficient.

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