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Vulnerability of smallholder farmers to ENSO-related drought in Indonesia

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ABSTRACT: Crop production in Southeast Asia is subject to considerable climate variability caused by the El Niño–Southern Oscillation phenomenon. El Niño causes comparatively dry conditions leading to substantial declines in 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 the present study is to assess the impact of El Niño on agricultural incomes of smallholder farmers in Central Sulawesi, Indonesia, and to derive suitable crop management strategies to mitigate income reductions. We identify 5 farm classes by cluster analysis. Our LP model maximises their cash balance at the end of the time period most severely affected by El Niño. Main activities are the cultivation of rice, maize and cocoa. Accounting for water supply, 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 policy relevant. The results illustrate that drought-related crop management recommendations must be tailored to farm households according to their location, farming system and resource endowment. Furthermore, our findings demonstrate the importance of policy measures aimed at an *ex post* alleviation of drought impacts.

KEY WORDS: ENSO · Risk management · Linear programming · Stochastic simulation · Indonesia

1. INTRODUCTION

Crop production in Southeast Asia is subject to considerable climate variability that is mostly attributable to the El Niño–Southern Oscillation (ENSO) phenomenon (cf. Salafsky 1994, Amien et al. 1996, Datt & Hoogeveen 2003). El Niño is associated with dry conditions: 93% of droughts in Indonesia between 1830 and 1953 occurred during El Niño years (Quinn et al. 1978). In 4 El Niño years between 1973 and 1992, the average annual rainfall amounted to only 67% of the 20 yr average in 2 major rice-growing areas on 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 affect the poor (Easterling et al. 2007, p. 283–284).

Several macro-scale studies model the impact of climate variability and climate change on crop production in the Asian Pacific region (see Zhao et al. 2005 for

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a review). However, in order to evaluate specific climate variability impacts and corresponding optimal agricultural adaptation strategies, it is crucial to study the associated systems at the community and household levels, as emphasised by the Intergovernmental Panel on Climate Change (Adger et al. 2007, p. 729). Against this background, the objective of the present study is to (1) quantify the impact of ENSO-related drought on crop yields and, hence, agricultural incomes in a rainforest margin area in Indonesia; (2) identify suitable crop management strategies for different climate scenarios, using linear programming (LP), and compare them with observed farmers' practices; and (3) 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 of the model outcomes, we produce more realistic probability distributions, whereby the downside risk of failing to achieve a specified minimum level of income provides a particularly policy-relevant 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 and model. Modelling results are presented in Section 5; in Section 6 results are discussed and conclusions drawn in Section 7.

2. RESEARCH AREA

The research area encompasses the Palu River watershed in Central Sulawesi Province, Indonesia. Its mountainous topography, ridges reach up to 2500 m a.s.l. (above sea level), results in a distinct rainfall gradient, with the coastal zone receiving only around 500 mm of rain per annum, while precipitation exceeds 3000 mm at higher elevations (WWF 1981). Due to the complex 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 3 subdistricts of Sigi Biromaru (50 to 90 m a.s.l.), Palolo (550 to 650 m a.s.l.) and Kulawi (560 to 980 m a.s.l.), which feature diverging climatic and hydrologic characteristics. Agricultural land use is also location specific, depending on local rainfall, topography and soil properties. Overall, irrigated rice and cocoa are the 2 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 (Indonesian Rupiah: US$ 1 = 8900 IDR, February 2003) 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.

Fig. 1 illustrates the ENSO-related variability of monthly rainfall in Central Sulawesi, showing that the June through October period is particularly affected; in the observed El Niño years rainfall is 62% of the average during this time period. Moreover, the distribution of rice planting times is displayed, i.e. the month when rice seedlings are transplanted from nursery seedbeds to the irrigable plots; while there are no clearly defined planting periods in equatorial climates, the distribution peaks in January/February for the first and in June to August for the second rice crop. Hence, the El Niño-related depression in rainfall largely coincides with the second cropping season. One month prior to transplanting, farmers establish seedbeds for raising the rice seedlings. Around the same time they start flooding their rice plots to facilitate soil preparation. Hence, access to ENSO forecasts 1 mo prior to the transplanting of the second rice crop, i.e. ideally in April, would allow farmers to adapt their cropping decisions accordingly.

3. METHODOLOGY

3.1. ENSO scenarios used in the model

Based on existing time series data of rainfall in Central Sulawesi we calculate the monthly precipitation anomaly of El Niño years in percentage relative to the long-term mean. Two graded El Niño scenarios are generated, which reflect the mean anomaly of all ob-

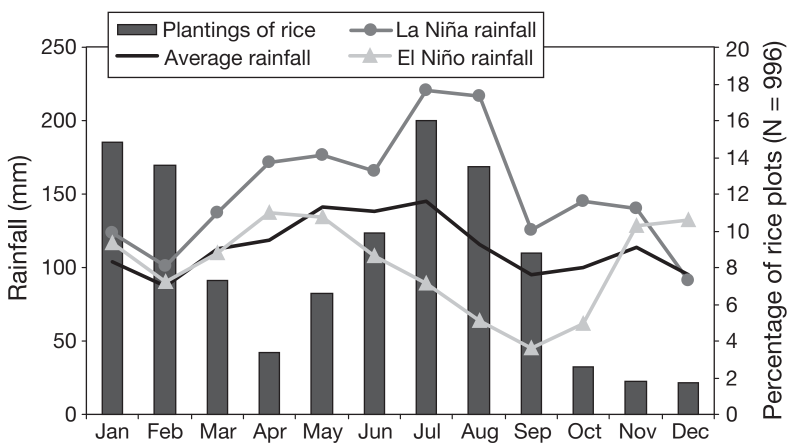

Fig. 1. El Niño–Southern Oscillation (ENSO)-related variation of monthly rainfall and temporal distribution of rice plantings in Central Sulawesi. Sources: our own survey (plantings); Dinas Pertanian Kabupaten Donggala (rainfall). Rainfall data are averages from 24 rain gauges throughout Central Sulawesi for 1981 to 1999; 1982, 1987, 1991, and 1997 are considered as El Niño, and 1988, 1996, and 1998 as La Niña years. From Keil et al. (2008)

served El Niño events (1987, 1991, 1994 and 1997), on the one hand, and the extreme El Niño event of 1997 on the other. Applying interpolation techniques, rainfall deviations in the 2 scenarios are calculated for the research villages, whereby the neutral year 2003[1] serves as a reference for 'normal' meteorological conditions (Gunawan 2006).

As a proxy for 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[2], resulting in the specific discharge (mm) available for irrigation in each research village (Leemhuis 2006). Table 1 summarises the rainfall and available irrigation water for the 3 scenarios 'Normal', 'Average El Niño', and 'Severe El Niño'.

Due to its location in the rain-shadow of 2 mountain ranges, the low-lying sub-district of Sigi Biromaru receives significantly less rainfall than the other 2 sub-districts. However, 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 6 mo period from 1 June to 30 November 2003 (the normal base year), total average rainfall was 1379 mm in Palolo and 1134 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 (irrigation water) during the base period was approximately 2900 mm in Palolo, it amounted to 6100 mm in the much larger Kulawi catchment. This deficit 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 3400 mm (56 %) in Kulawi.

3.2. Modelling the effect of El Niño on crop yields

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

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

[1]Based on the Southern Oscillation Index (BOM 2007)

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

Table 1. Rainfall and available irrigation water in Central Sulawesi during the period 1 June to 30 November for 3 climate scenarios: normal year 2003; mean of the El Niño years 1987, 1991, 1994 and 1997; El Niño year 1997. In brackets: percent of 'normal' value

Climate scenario	Sub-district	Rainfall (mm)	Irrigation water (mm)
Normal	Sigi Biromaru	539 (100)	7872 (100)
	Palolo	1379 (100)	2904 (100)
	Kulawi	1134 (100)	6110 (100)
Average El Niño	Sigi Biromaru	341 (63)	4286 (54)
	Palolo	675 (49)	847 (29)
	Kulawi	790 (70)	4568 (75)
Severe El Niño	Sigi Biromaru	248 (46)	3751 (48)
	Palolo	627 (45)	808 (28)
	Kulawi	565 (50)	3407 (56)

where $\ln Y$ is the natural logarithm (ln) of the output; i is the household index (i = 1,…, N; N = 113, 97 and 34 for rice, cocoa and maize, respectively); t is the time index (t = 1,…, T_{max}, T_{max} = 4 cropping seasons for rice and maize, T_{max} = 2 yr for cocoa); β is a vector of parameters to be estimated; D_m is a vector of dummy variables; $\ln X_k$ is the natural log of the input vector, including climate related variables; and ε is an $N(0, \sigma_\varepsilon)$ 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 for 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 1 in the case of a 'zero-observation' of the corresponding explanatory variable, and the value of 0 otherwise.

3.3. Simulating cropping strategies using linear programming

To include the effects of changing resource allocation in the analysis 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, rather than to optimise resource allocation under present conditions. 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 & 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

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 Eq. (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 Eq. (1) these stochastic yield components, along with measurement errors[3], 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 the latter is to generate random numbers that match the true residuals in terms of functional form, mean and SD, whereby the validity of the simulation outcome can be tested (Law & Kelton 2000).

Using this approach, we derive 2 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). (2) In addition we derive 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 this allows 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 Eq. (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 various 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. HOUSEHOLD MODEL AND DATA

4.1. 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 sub-periods, balances are calculated for labour, cash and outputs. The model objective is to maximise the amount of cash in the last period. The determination of cropping patterns takes 3 types of crop land into account: irrigated and non-irrigated land for annual crops[4] as well as cocoa plantations. Household labour capacity and household food requirements also critically determine model outcomes. All 3 major crops can be grown at 3 levels of production intensity, namely mean observed level of input use, and 75 and 125% of observed level. The respective output levels are calculated via the estimated production functions. There is

[3] In our analysis, measurement error is not considered, as it is assumed to be of minor relevance: farmers know 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.

[4] Rice can only be grown on irrigated land, all other crops can be grown on all annual crop land.

no statistically significant evidence that the reduced supply of either rice or cocoa led to an increase in farm gate prices mitigating the impact of reduced yields on agricultural income (Keil et al. 2008; see Section 6); hence, constant prices are assumed. Rice and maize can be planted during 2 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 to 6 mo vegetation period (Rehm & Espig 1991: p. 95 and 99), they are assumed to produce full yields even 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 out loans and the sale and purchase[5] of outputs.

In the case of rice, we correct for a limitation in the estimation of the production function by introducing a minimum water availability threshold as an additional production constraint to adequately account for its water requirements (see Section 5.1); 10 mm water d^{-1} are required to irrigate a rice crop (IRRI 2005). In our model, rice can only be grown if total water supply from rainfall and irrigation exceeds 1000 mm during the cropping season. This threshold takes into account that growing rice is still feasible at somewhat sub-optimal levels of water supply, since the average vegetation period of rice is 120 d in the research area, corresponding to a total water demand of 1200 mm.

4.2. Data

In early 2003, socioeconomic data were collected in a stratified random sample of 228 farm households. To capture the variation in local climatic conditions, 8 out of the 53 villages located in the Palu River watershed were randomly selected using elevation a.s.l. as a stratification criterion. In a second step, farm households were randomly selected in these villages, using lists of households based on the most recent village census. Apart from capturing households' resource endowment, data were collected on household-level effects of an ENSO-related drought, as well as mitigation and coping strategies applied[6]. In early 2005 crop production data were collected from the same sample covering the years 2003 and 2004, i.e. 2 years of cocoa production and up to 4 cropping seasons of rice and maize. For the same time period, rainfall data are available from weather stations set up in each research village and discharge data from hydrological instruments installed at key locations of the watershed, which feed into the production functions of the 3 major crops[7] (see Section 3.2). The total numbers of observations are 408, 190 and 79 for rice, cocoa and maize production, respectively. Output levels and input requirements of soybeans and groundnuts, the 2 alternative crops considered, are based on secondary data from the local agricultural extension service.

4.3. 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 2 separate cluster analyses, one on the 96 survey households from the low-lying sub-district of Sigi Biromaru, and the other 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: 4 classes in the low-lying sub-region and 5 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.

To focus on the differences in household reactions to climate variation, only the 4 most disparate household classes are considered in the subsequent analysis, which are Classes L1 and L2 in the low-lying area and Classes U1 and U2 in the upland area. L1 households are characterised by small farm size and an emphasis on rice production. Households in Class L2 crop larger areas and are less rice based. Farms in Class U1 are medium sized with mixed cropping patterns and some emphasis on cocoa, while Class U2 is similarly sized but highly specialised on cocoa. To account for differences in climatic and hydrologic conditions between Palolo

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

[6]When collecting these data the following rule was applied: first, the most severe drought period experienced by each household was identified, the remainder of the interview then referred to this event; in cases of several droughts of equal perceived severity, the most recent period was chosen in order to minimise recall bias. Applying this rule, 70% of the interviews were based on an ENSO-related drought in 2002, i.e. an event experienced only months prior to the survey. Only 8% of the interviews involved a recall period of >5 yr.

[7]All instruments were installed in late 2002. Therefore, matching rainfall and discharge data are not available for cropping seasons prior to 2003.

Table 2. Results of the cluster analysis, indicating mean values of the clustering variables for 9 Household Classes L1 to U5. Subsequent analysis focused on Household Classes L1, L2, U1 and U2 (in **bold**). HH: household; AE: adult equivalents; IDR: Indonesian rupiah (US $ 1 = 8900 IDR)

	Cluster notation (N)	Drought impact index[a]	Cropped area (a)	HH labour capacity (≥10 yr of age) (AE)	Irrigated rice area per cropped area (%)	Cocoa area per cropped area (%)	Poverty index[b]	Total off-farm income (10^3 IDR)
Lowland	**L1 (37)**	**3.5**	**90**	**2.7**	**90**	**2**	**–0.17**	**971**
	L2 (15)	**4.1**	**320**	**3.9**	**42**	**26**	**1.21**	**1751**
	L3 (16)	3.7	119	3.5	27	52	–0.38	992
	L4 (23)	3.7	84	2.9	12	2	–0.25	963
Upland	**U1 (19)**	**2.4**	**177**	**5.0**	**27**	**38**	**0.53**	**5405**
	U2 (34)	**1.8**	**182**	**3.3**	**3**	**80**	**0.66**	**1125**
	U3 (27)	3.6	122	2.3	15	37	–0.93	972
	U4 (25)	3.2	150	3.3	67	17	–0.46	774
	U5 (20)	2.6	493	4.2	23	22	–0.03	553

[a]Perceived effect of the most severe drought experienced by the household, on a scale from 0 (no effect) to 5 (very serious) (Keil 2004)

[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 SD of 1 (Keil 2004)

and Kulawi (cf. Table 1), Class U1 is duplicated with one version (denoted U1P) being linked to the production functions and climate scenarios defined for Palolo and the other (denoted U1K) being linked to Kulawi.

The means of resource endowment variables (e.g. total annual crop land, irrigated crop land, cocoa plantation land, family labour capacity) within these classes are utilised by the LP model as resource constraints. Similarly, the input requirements of cropping activities (e.g. seeds, fertiliser, herbicides, labour) as well as household needs (e.g. rice, cash) within the LP model are determined by cluster means. As data on total family labour utilisation are not available, an availability coefficient of family labour for actual cropping activities of 40% is assumed.

5. RESULTS

5.1. Modelling the effect of El Niño 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 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.

5.1.1. Effect of rainfall on rain-fed crops

Based on the regression coefficients of the variables rain, rain squared and water, crop yields can be calculated for different rainfall scenarios. Fig. 2 illustrates the relationship between rainfall and yield for the rain-fed 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.

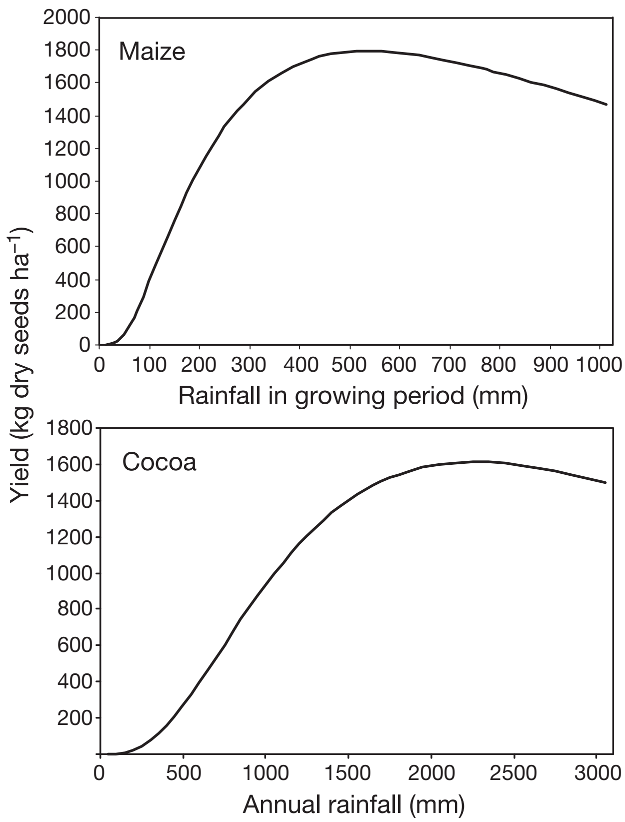

Fig. 2. Relationship between rainfall and yield for maize (top) and cocoa production (bottom) in Central Sulawesi, Indonesia, based on empirically estimated production functions

Table 3. Variables used in the estimation of production functions for irrigated rice, maize, and cocoa in Central Sulawesi, and their summary statistics. IDR: Indonesian rupiah (US $ 1 = 8900 IDR)

Variable	Definition	Rice		Maize		Cocoa	
		Mean	SD	Mean	SD	Mean	SD
Dependent[a]							
Output	Logged total crop output (kg of husked rice, dry maize seeds, or dry cocoa seeds)	978.42	825.09	907.11	1010.80	904.04	999.03
Continuous independent[a]							
Land	Logged total input of land (a)	67.26	46.60	53.58	30.38	106.04	94.46
Labour	Logged total input of labour (manhours)	–		118.22	88.00	460.46	420.53
Seeds	Logged total input of rice seed (l)	86.51	58.90	–		–	
Fertiliser	Logged total input of fertiliser/herbicides/	109335.89	130951.43	74035.44	117346.16	–	
Herbicides	all materials (IDR)	33718.72	46561.83	–		–	
Materials		–		–		360146.76	874941.76
Rain	Logged total amount of rainfall (mm)[b]	–		469.87	208.47	1790.46	635.26
Water	Logged total amount of rainfall and available irrigation water[c]	2893.15	1605.25	–		–	
Temperature	Logged mean annual temperature (°C)	–		–		24.73	1.58
Age	Logged weighted mean age of the cocoa plantation (yr)	–		–		8.94	3.52
Dichotomous independent							
Pests/diseases	Dummy = 1 if yield was drastically reduced by pests/diseases, 0 otherwise	0.19	0.39	0.09	0.29	0.38	0.49
High-yielding variety	Dummy = 1 if high-yield variety was used, 0 otherwise	0.07	0.25	–		–	
Several plots	Dummy = 1 if household cultivates several plots, 0 otherwise[d]	–		–		0.35	0.48
No fertiliser	Zero-observation dummy = 1 if fertiliser/	0.12	0.33	0.49	0.50	–	
No herbicides	herbicides/materials is zero, 0 otherwise	0.20	0.40	–		–	
No materials		–		–		0.40	0.49

[a]Summary statistics of untransformed data
[b]During the cropping season (maize)/during the year (cocoa)
[c]During the cropping season (mm)
[d]Plots often differ significantly in terms of location and, hence, micro-climatic and soil characteristics

5.1.2. Effect 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 small. It indicates that rice yield 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

Fig. 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 Eq. (1). As a first step, the distribution of ε is tested for normality: the null-hypothesis of a normal distribution is accepted for all 3 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 Eq. (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 Mg ha^{-1} for rice, 6 Mg ha^{-1} for maize and 5 Mg ha^{-1} for cocoa. According to the local agricultural extension service, these are the maximum yields that can 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 3 cases, the independent-samples *t*-test fails to reject the null-hypothesis

Table 4. Ordinary least-squares estimates of the parameters in the Cobb-Douglas production functions for rice, maize and cocoa production in Central Sulawesi. *p = 0.05, **p = 0.01, ***p = 0.001

Variable	Rice		Maize		Cocoa	
	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
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***	–		–	
Fertiliser	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***
High yield variety	0.201	2.682**	–		–	
Several plots	–		–		0.297	2.520*
No fertiliser	1.255	3.829***	3.285	2.388*	–	
No herbicides	0.955	3.294**	–		–	
No materials	–		–		0.946	1.502
N	408		79		190	
F	165.966***		39.747***		72.949***	
R^2	0.790		0.797		0.803	
Adjusted R^2	0.785		0.777		0.792	

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 3 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, Fig. 3 displays the drought impact on the yield of cocoa in Sigi Biromaru, 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 3 scenarios are those attained with a cumulative probability of 50%, showing that mean cocoa output during the 6 mo period from 1 June to 30 November declines from 530 kg ha^{-1} of dried beans under 'normal' conditions to 241 and 114 kg ha^{-1} during an average and a severe El Niño event, respectively. Furthermore, the figure displays the probabilities of attaining an output level of 250 and 500 kg ha^{-1} under the 3 climate scenarios; while the probability of failing to attain an output of 250 kg ha^{-1} is only 16% in a 'normal' year, it increases dramatically to 54 and 86% in the average and severe El Niño scenarios, respectively. In Palolo the respective probabilities are substantially lower at 14, 35 and 41%, and in Kulawi they are the lowest at 13, 19 and 39%, highlighting the differences in the local impact of El Niño within the research area.

5.3. Deterministic model output: optimal resource allocation

Fig. 4 displays the LP model solution with regard to the allocation of land for different cropping activities and production intensities for a normal year and a severe El Niño season in the lowland Household Classes L1 and L2; in the normal scenario, L1 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% is planted 1 mo later.

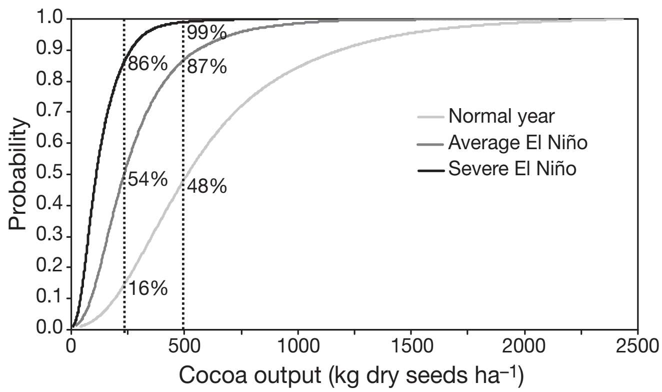

Fig. 3. Cumulative distribution functions of cocoa yields during June to November in Sigi Biromaru sub-district, Central Sulawesi, during normal, average El Niño and severe El Niño years

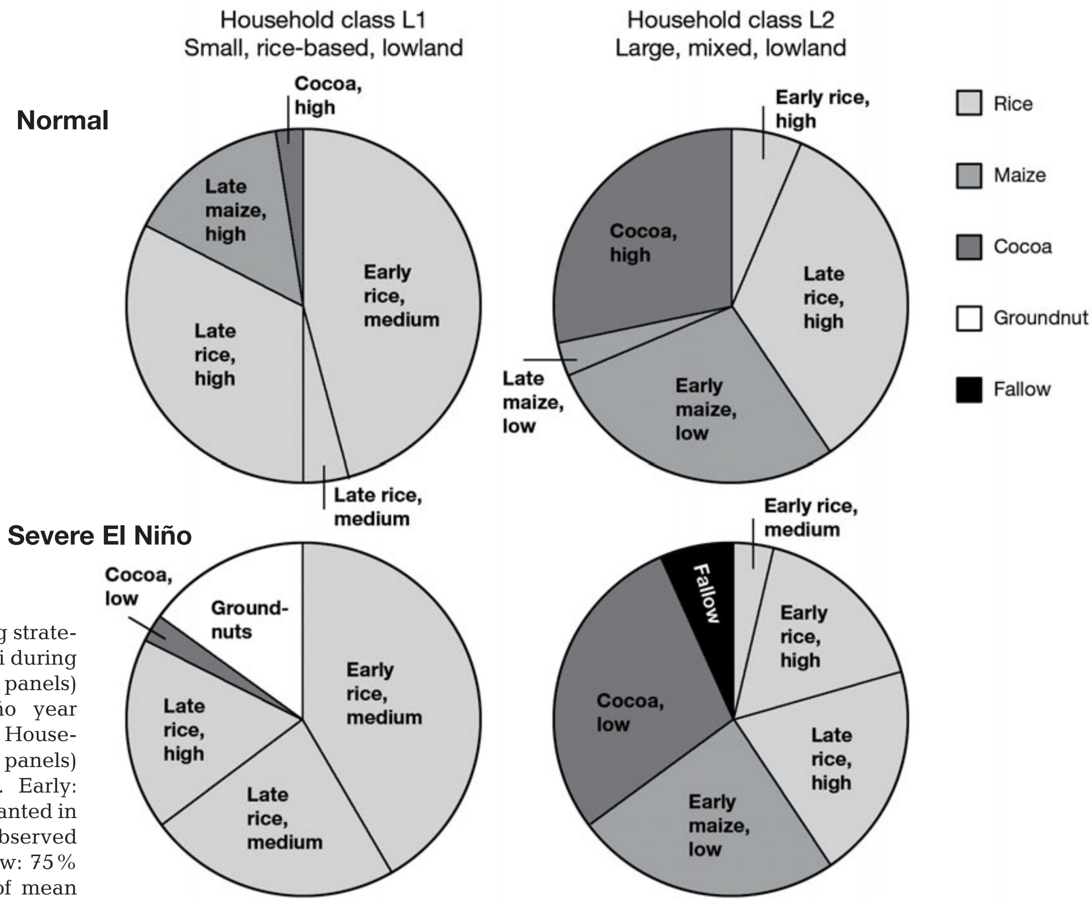

Fig. 4. Optimal cropping strategies in Central Sulawesi during a normal year (upper panels) and a severe El Niño year (lower panels) for farm Household Classes L1 (left panels) and L2 (right panels). Early: planted in June; late: planted in July; medium: mean observed production intensity; low: 75% of mean; high: 125% of mean

Furthermore, a 'medium' input intensity is adopted for the early rice, whereas the 'high' intensity level is applied to most of the late rice[8]. Household Class L2 allocates 41% of the cropping area to rice, 31% to maize and 28% to cocoa. 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, the model predicts that L1 reduces the input intensity on most of its late rice and on its cocoa, and that maize is replaced by groundnuts, a more drought-tolerant crop. Household Class L2 is also expected to reduce input intensities in cocoa production and some share of rice, and to adjust the planting dates of rice; part of the land that is normally planted with 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.

Regarding the upland Household Classes U1P and U1K, which feature identical socio-economic characteristics, but differ in terms of location, the more favourable hydrologic conditions in Kulawi (cf. Table 1) have important implications: in the normal scenario both household classes dedicate 25% of their cropping area to rice and 22% to maize, while 53% are occupied by cocoa. During the severe El Niño scenario, U1K can continue to grow rice and replace maize with more drought-tolerant soybeans. In contrast, it is not possible for U1P households to continue growing rice, since the minimum water requirement of 1000 mm during the 120 d 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 to continue maize cultivation on 5%. The total water supply in the Palolo valley during the first 100 d after transplanting, when rice is particularly sensitive to water stress (IRRI 2005), is estimated at 410 mm for the average El Niño and 390 mm for the severe El Niño scenario. Therefore, rice cultivation is clearly not a viable option.

Fig. 5 visualises the susceptibility towards drought-induced income reductions, as well as the effect of the adaptation measures produced by our model. For reasons of clarity, only the normal and severe El Niño scenarios are depicted, results on income reductions in the average El Niño scenario are provided in the text.

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

To make income levels comparable across household classes, the total agricultural income generated in the 6 mo simulation period is converted into US $ per adult equivalent (AE) per day; an AE is based on caloric requirements, differentiated by gender and age (WHO/FAO 1973). While the daily agricultural income of L1 is the lowest at 0.41 US $ AE^{-1} during the normal scenario, it is also the most stable; in the average and the severe El Niño scenarios income is reduced to 83 and 78 % of the 'normal' level, respectively. At 1.64 US $ AE^{-1} the daily agricultural income of the cocoa-based Household Class U2 is the highest, followed by the large, diversified L2 farms (1.40 US $ AE^{-1}). However, both classes experience considerable income reductions in the 2 El Niño scenarios, at 60 and 44 % of the 'normal' level for L2, and 54 and at 47 % for U2, respectively. While daily incomes of Household Classes U1P and U1K are similar under normal conditions, 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 2 El Niño scenarios, as opposed to 80 and 54 % in the case of their Kulawi counterparts.

However, the considerable changes to cropping patterns and production intensities recommended by the model to alleviate the impact of El Niño-induced drought should be viewed with caution. A comparison of the optimised results with those generated without adapting cropping strategies reveals that in the severe El Niño scenario adaptation increases agricultural income by only 0.6, 5.5, 2.9 and 3.2 % for Household Classes L1, L2, U1K and U2, respectively. Only the households in Class U1P benefit substantially with an income increase of 46 %; adjusting their agricultural practices enables them to maintain 39 % of their agricultural income compared to a normal year, rather than 27 % without adapting. Due to the lack of reliable irrigation facilities in this area, rice fails completely during El Niño years. Therefore, planting soybeans and groundnuts instead of rice is particularly beneficial.

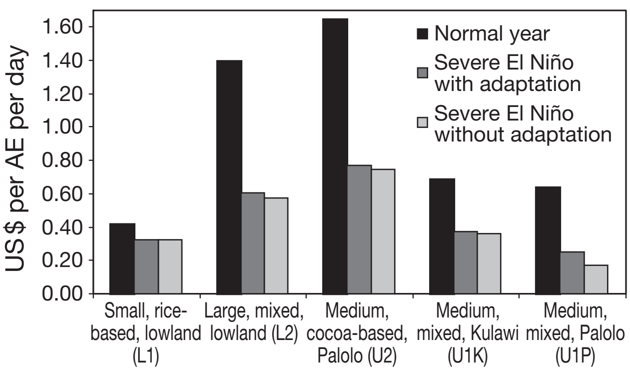

Fig. 5. Agricultural income levels in US $ per adult equivalent (AE) per day (AE are based on caloric requirements, differentiated by gender and age; WHO/FAO 1973) for the period 1 June to 30 November

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

The cumulative distributions of cash and credit levels displayed in Fig. 6 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. Fig. 3 for the example of cocoa). The graph depicts the cumulative distribution functions under the normal and the severe El Niño scenarios. Positive values on the *x*-axis correspond to cash levels obtained by the end of the 6 mo simulation period, while negative values reflect total credit requirements during the same period. The latter are of particular interest in view of the fact that credit is almost exclusively available from informal sources at very high interest rates (see Section 6).

In addition to the deterministic results displayed in Fig. 5, we can now derive information on the levels of risk involved in the cropping systems practised. For example, the distribution functions of Household Classes L2 and U2 cross each other under both climate scenarios. This indicates that the cropping strategy of U2 households, which devote 80 % of their cropping area to cocoa and are therefore highly specialised (cf. Table 2), involves a higher level of risk than the more diversified crop portfolio of L2 households. By disregarding the lower and upper 10 %-tails of the distribution functions, one can state that with a probability of 80 % L2 incomes will be from 4.5 to 14.0 million IDR, whereas U2 incomes will range from 3.3 to 15.8 million IDR. With a probability of roughly 70 % in the normal and 50 % in the El Niño scenario, L2 will achieve a higher level of income than U2.

Furthermore, the graph shows that households in Class L1 with certainty require credit for financing agricultural inputs in both climate scenarios. Class L2 can do without a loan with a probability of around 75 % during 'normal' years, but this probability declines to <10 % in the severe El Niño scenario. Moreover, in the drought scenario, L2 needs to borrow a larger sum than L1, with a probability of around 80 % (the 2 functions intersect at a probability level of 0.20). Also for Classes U1P and U1K the risk of having to take a loan significantly increases from around 5 % under 'normal' to roughly 30 % under drought conditions, but the amount that has to be borrowed is relatively small. Only the cocoa-based Household Class U2 never relies on credit to finance agricultural inputs due to a continuous flow of revenue from sales every 2 wk of dried cocoa beans.

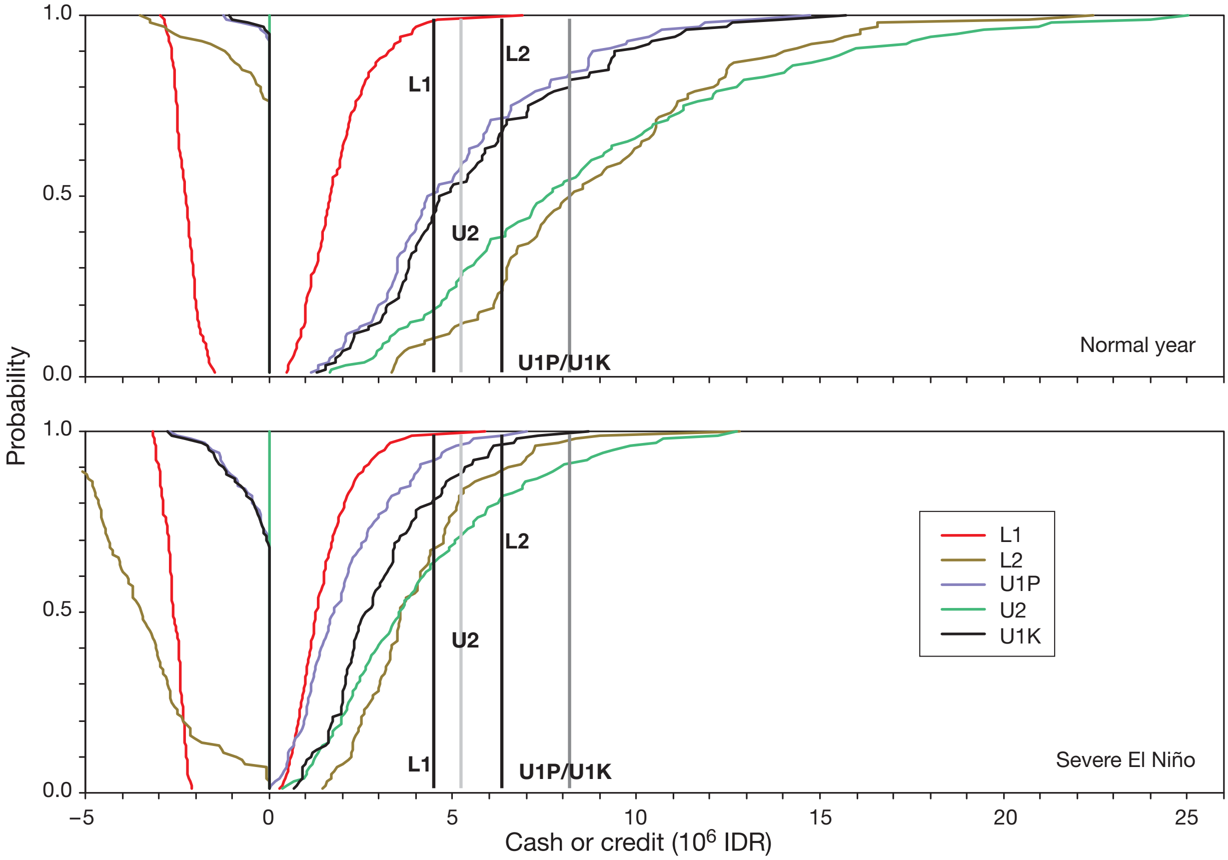

Fig. 6. Cumulative distribution functions of the cash levels attained (positive values) and total credit requirements (negative values) over the period 1 June to 30 November in a normal year (upper panel) and a severe El Niño year (lower panel), accounting for stochastic yield fluctuations. The vertical lines correspond to a 1 US $ per adult equivalent per day income threshold. 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 for rice, maize and cocoa

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 Fig. 6 mark an agricultural income level of 1 US $ d^{-1} per AE[9]. Since household classes differ in their demographic composition (except U1P and U1K), different total cash levels correspond to this threshold. The graph shows that L2 and U2 households exceed the threshold with a probability of roughly 75% during 'normal' years, Household Classes U1P and U1K have a chance of 15 to 20% to do so, and for L1 households the chance is negligible. However, during El Niño, all household classes are very likely to fall beneath the 1 US $ threshold, whereby, at 90%, the probability is higher for the mixed L2 households than for the cocoa-based U2 households (70%).

[9]This is not identical with the poverty line used by international institutions, since it is not adjusted for purchasing power parity and does not consider off-farm income.

6. DISCUSSION

6.1. Modelling the effect of El Niño on crop yields

Our approach of using regression analysis to estimate the relationship between rainfall and crop yields proves successful in the case of the rain-fed crops maize and cocoa. The empirically estimated yield maximum at 525 mm of rainfall per growing season in the case of maize and 2200 mm yr^{-1} in the case of cocoa is consistent with values found in the literature (Franke 1994a: p. 76, 1994b: p. 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 impact of water supply on rice yields. This is probably due to the fact that farmers will reduce the area planted with rice under drought conditions and attempt to adequately irrigate the remaining rice plots. Thus, drought affects the area harvested rather than the 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 limited variability in the dataset 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.

6.2. Identifying optimal crop management strategies

In general, an optimal adaptation of cropping activities to drought conditions comprises 2 elements. (1) Production intensities of traditionally grown crops should be reduced. 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. (2) If the yields of the annual crops rice and maize fall below a certain threshold level, or if the specified minimum water supply of 1000 mm for a rice crop cannot be met, these crops should be replaced by more drought-tolerant alternatives. While the simulations do reflect these general adaptation strategies, the main value of the model lies in indicating how adaptation strategies may differ between household classes, depending on their resource endowment and the micro-climatic and hydrologic characteristics of their environment. For example, different strategies apply to the 2 lowland Household Classes L1 and L2 because of differences in their crop portfolios as well as their endowment with land, labour and capital. Different strategies also apply to the 2 upland Household Classes U1P and U1K due to differences in the climatic and hydrologic conditions of their locations; these differences could only be identified through the inclusion of hydrologic modelling results, thus illustrating the added value of an interdisciplinary modelling approach. However, the mitigation of average income losses enabled by adapting cropping patterns and intensities as simulated by the model remains limited in all but one of the household classes.

6.3. Modelling the effect of drought on agricultural incomes

There is empirical evidence that drought-induced declines in crop yields are not significantly mitigated by local price effects. For instance, the sample farmers received 2076 IDR kg^{-1} of rice during the climatically normal first cropping season of 2002 and 2147 IDR during the second cropping season, when significant production depressions were experienced due to El Niño. The difference is not statistically significant, and in both seasons the minimum and maximum prices received were 1500 and 2500 IDR, respectively. The lack of price effects may be explained by the heterogeneity of both climatic conditions and irrigation facilities within the research area, with localised drastic reductions in rice supply having only a limited effect on regional market supply. In the case of the primary cash crop cocoa, prices are, of course, largely determined by world market conditions rather than the local supply.

The LP model shows that 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 (L1) 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 catchment area. On the other hand, the relatively wealthy cocoa-based farmers (U2) are highly susceptible to drought, suffering an income loss of around 50%. The example of Household Classes U1P and U1K 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 U1P particularly prone to drought-induced income depressions.

6.4. 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, which varies widely between household classes; for example, the level of risk is relatively low when agricultural production is based on rice in a technical irrigation system with a relatively reliable water supply (L1) and relatively high in cases of cocoa-based farming systems (U2).

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 L2 and U2 are capable of generating average agricultural incomes >1 US \$ d^{-1} AE^{-1}. During El Niño all household classes are very likely to fall beneath the 1 US $ threshold, whereby the mixed L2 households prove more vulnerable than the cocoa-based U2 households. Hence, while U2 households are susceptible to 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 in the research area off-farm income is of only minor importance. Moreover, sources of off-farm income are mainly agricultural wage labour or locally marketed goods and services; 51% of the sample households receive income from wage labour; in two-thirds of these cases this is agricultural labour, usually in the same or a neighbouring village (Keil et al. 2008). Hence, wage labour income is directly affected by drought in most cases. Overall, 19% of households generate non-agricultural income through self-employment; in 37% of these cases, households run a local kiosk, and the goods and services provided by the remaining households are also marketed at a local level (Keil et al. 2008). Therefore, when the local agricultural income declines due to drought, the demand for these goods and services is likely to decrease, thus negatively affecting non-agricultural income as well, which is in line with the observations made by Fafchamps et al. (1998).

6.5. Comparison of the modelling results with empirical findings

For the normal scenario the LP results closely correspond to the observed cropping patterns as indicated by the survey data; while the observed area shares of rice and cocoa are exactly replicated by the base model[10], the area allocated to maize is, on average, overestimated by 13%. This is because maize is the only rain-fed annual crop included in the model, whereas the interviewed households also cultivate a range of minor crops, such as vegetables and cassava. These are not considered in the model because of data constraints.

According to the survey data, 209 out of 228 respondent farmers (92%) had previously experienced drought conditions, which in 188 cases (90%) affected crop yields; on average, rice production declined to 64% and cocoa production to 62% of the levels attained in climatically 'normal' years, resulting in a decline of agricultural income to 51% of the 'normal' level for the average farm household[11] (Keil 2004: p. 71–79). Relative to the 'normal' scenario, the modelled agricultural income levels across all household classes[12] without adaptation are 59% for the average El Niño and 48% for the severe El Niño scenarios, which correspond very well with the empirical findings.

Despite this significant income depression, agricultural adaptation measures are scarcely practiced; only 16% of the drought-affected farmers changed the area share of different annual crops, e.g. they grew maize instead of rice, and only 15% reported that they reduced the amount of inputs applied to their crops (Keil 2004: p. 86). With regard to production intensities, the 'medium' intensity level predicted by the model for most annual crops in the El Niño scenarios corresponds to the current practice as determined by the survey. For the normal scenario, however, the model recommends the 'high' input level for nearly all crops in all classes except for Class L1. A possible explanation for this difference is that risk-averse smallholders avoid higher intensities for fear of unpredictable yield losses, e.g. due to drought, pests, or diseases, resulting in a sub-optimal level of input use where the marginal returns exceed the marginal costs. Hence, both during El Niño and climatically 'normal' years, the majority of farmers follows a 'standard' crop management procedure without adjusting planting dates, crop area shares, or input supply. This observed lack of adaptation may partly be explained by a lack of information: only 20 respondents (10%) reported that they had information about the likely occurrence of a drought at the time when cropping decisions had to be made, out of which only 9 farmers (4%) had received this information from an official source, such as the agricultural extension service, while the remainder relied on indigenous knowledge (Keil 2004: p. 84). However, as elaborated in Section 5.3, the LP results indicate that only for Household Class U1P would the adaptation of cropping activities considerably reduce drought-related income losses. The other classes would gain only marginally through 'optimised' cropping patterns. This implies that for most farm households in Central Sulawesi it is probably quite rational to adhere to a 'business-as-usual' crop management strategy even during El Niño years. In this regard, our modelling results are also consistent with the empirical observations.

[10] The area share of the perennial crop cocoa is fixed and that of rice is determined by the availability of irrigable land; here, due to its higher gross margin and its importance for home consumption, rice is preferable to any other annual crop during climatically 'normal' conditions.

[11] In 70% of cases these data refer to a drought experienced in 2002 (see Section 4).

[12] Mean values weighted by the relative frequencies of the household classes.

The lack of adaptation[13] means that risk management is mostly confined to *ex post* coping strategies: in order to smooth consumption despite their reduced agricultural income, 43 % of the affected households earned income from sources that are not usually utilised, the primary additional income sources being temporary employment (72 %) and the sale of rattan collected in the adjacent Lore Lindu National Park (28 %, multiple responses possible). Furthermore, 21 % obtained a consumption loan from informal sources such as traders and shopkeepers who charged an annual interest rate of 64 % on the average, ranging up to 400 % (Keil et al. 2008). Real interest rates in excess of 100 % for informal credit have been confirmed by Zeller et al. (1997). Access to formal credit at moderate interest rates — also for production purposes — is very limited in the research area. This underlines the significance of the drought-induced increase in production credit requirements as illustrated in Fig. 6. The high interest rates charged imply that drought increases the risk of farmers to become indebted and, hence, trapped in poverty.

Despite the coping efforts outlined above, 62 % of the sample households had to reduce expenditures for basic necessities as a consequence of severe drought periods, whereby off-farm income is found to have had no significant effect on the households' ability to smooth consumption (Keil et al. 2008). These effects of drought are well reflected by our modelling results: although our illustrative 1 US $ threshold does not correspond to the international poverty line, it is obvious that El Niño-related drought drastically increases the probability of failing to meet minimum household requirements.

7. CONCLUSIONS AND RECOMMENDATIONS

The model simulations show that El Niño-related drought leads to drastic declines of crop yields and, hence, agricultural incomes in Central Sulawesi, which is confirmed by empirical data. 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 might 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, such as soybeans or groundnuts. However, our model results indicate that the potential to reduce drought-induced income losses through agricultural adaptation strategies under the current irrigation conditions is very limited for most types of farm households in the area, which is in line with the observed lack of such adaptation measures. From this we conclude that, while it is important to enhance farmers' capacity to apply *ex ante* measures for drought impact mitigation, policy measures aimed at alleviating the unavoidable negative consequences of drought *ex post* will also remain of crucial importance.

With regard to adaptation, improved access to ENSO forecasts in the research area would give farmers a better chance of taking precautions before the onset of a drought. Here, a particular research challenge lies in the development of climate models with acceptable levels of accuracy for mountainous regions such as Central Sulawesi. However, even access to a more general ENSO warning system would at least sensitise farmers, and they may then be able to judge from experience to what extent they will be affected by drought conditions, depending on their farming system and particular location. This information could be disseminated through mass media, as well as via the agricultural extension service. Before a particular alternative crop can be recommended as an adaptation strategy, a thorough assessment of its agronomic and marketing potential under the specific frame conditions of a given area is of crucial importance.

With regard to the alleviation of drought impacts, we conclude that formal financial institutions should be promoted to enable farmers to access credit at moderate interest rates: our model simulations illustrate the increased need for production credit during drought periods, and the empirical findings show that there is an increased demand for consumption credit by poor households that are particularly likely to be caught in a poverty trap through the exorbitant interest rates charged by informal lenders.

By highlighting the diversity among farm households and its implications on El Niño impacts, we demonstrate that a uniform policy is not appropriate regarding climate impact mitigation in an area characterised by a high degree of agro-ecological and socio-economic diversity. By identifying farming systems and sub-regions where production is most severely affected by El Niño events and where the risk of falling into poverty is the greatest, the research results enable technical interventions and support policies to be better targeted and thus more effective and economically efficient.

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[13]Apart from sub-optimal input intensities which may be viewed as an adaptation to frequent drought.

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