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PRICE VS. WEATHER SHOCK HEDGING FOR CASH CROPS: EX ANTE EVALUATION FOR COTTON PRODUCERS IN CAMEROON

Antoine LEBLOIS
Philippe QUIRION
Benjamin SULTAN

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DEPARTEMENT D'ECONOMIE
Route de Saclay
91128 PALAISEAU CEDEX
(33) 1 69333033
http://www.economie.polytechnique.edu/
mailto:chantal.poujouly@polytechnique.edu

Price vs. weather shock hedging for cash crops: ex ante evaluation for cotton producers in Cameroon

Antoine Leblois*, Philippe Quirion† and Benjamin Sultan‡

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Abstract

In the Sudano-sahelian zone, which includes Northern Cameroon, the inter-annual variability of the rainy season is high and irrigation is scarce. As a consequence, bad rainy seasons have a detrimental impact on crop yield. In this paper, we assess the risk mitigation capacity of weather index-based insurance for cotton farmers. We compare the ability of various indices, mainly based on daily rainfall, to increase the expected utility of a representative risk-averse farmer.

We first give a tractable definition of basis risk and use it to show that weather index-based insurance is associated with a large basis risk. It has thus limited potential for income smoothing, whatever the index or the utility function. Second, in accordance with the existing agronomical literature we find that the length of the cotton growing cycle, in days, is the best performing index considered. Third, we show that using observed cotton sowing dates to define the length of the growing cycle significantly decreases the basis risk, compared to using simulated sowing dates. Finally we found that the gain of the weather-index based insurance is lower than that of hedging against cotton price fluctuations which is provided by the national cotton company. This casts doubts on the strategy of international institutions, which support weather-index insurances in cash crop sectors while pushing to liberalisation without recommending any price stabilization schemes.

Keywords: Agriculture, weather, index-based insurance.
JEL Codes: O12, Q12, Q18.

*Laboratoire d'économetrie de l'École Polytechnique, CIRED (Centre International de Recherches sur l'Environnement et le Développement), leblois@centre-cired.fr.

†CIRED, CNRS.

‡LOCEAN (Laboratoire d'Océanographie et du Climat, Experimentation et Approches Numériques).

Contents

1 Introduction

According to Folefack et al. (2011), cotton is the major cash crop of Cameroon and represents the major income source, monetary income in particular, for farmers (more than 200 000 in 2010) of the two northern provinces: *Nord* and *Extrême Nord*. It is grown by smallholders with an average of about 0.7 hectares per farmer dedicated to cotton production in the whole area representing about 150 000 hectares in 2010.

Traditional agricultural insurance, based on damage assessment, cannot efficiently shelter farmers because they suffer from an information asymmetry between the farmer and the insurer, creating moral hazard, and requiring costly damage assessment. An emerging alternative is insurance based on a weather index used as a proxy for crop yield (Berg, Quirion and Sultan, 2009). In such a scheme the farmer pays an insurance premium every year and receives an indemnity if the weather index falls below a determined level (the strike). Weather index-based insurance (WII) does not suffer from the two shortcomings mentioned above: the weather index provides an objective, and relatively inexpensive, proxy of crop damages. However, its weakness is the basis risk that comes from the imperfect correlation between the weather index and the yields of farmers contracting the insurance.

This paper therefore aims at assessing WII contracts in order to shelter cotton farmers against drought risk (either defined on the basis of rainfall, air temperature or satellite imagery). Insurance indemnities are triggered by low values of the index supposed to explain yield variation. Insurance allows to pool risk across time and space in order to limit the impact of weather (and only weather) shocks on producers income.

A recent but prolific literature about WII in low income countries has analysed the impact of pilots programmes through ex post studies. The most robust empirical finding is the low take up rate of those products. Several explanations have been proposed: steep price elasticity; existing informal risk sharing networks (Karlan et al., 2012; Mobarak and Rosenzweig, 2012 and Cole et al., forthcoming); lack of trust or financial literacy (Hill, Hoddinott and Kumar, 2011; Cai, de Janvry and Sadoulet, 2012 and Giné, Karlan and Ngatia, 2012) and ambiguity aversion (Bryan, 2010).

Yet a simpler explanation may be that the benefit of WII is simply too low given the basis risk and the costs of running the scheme. Surprisingly few assessments of the benefits from, and basis risk of, WII exist. Thus, in this paper, we look at the potential benefit cotton farmers could gain from index insurance and at the basis risk associated with various weather indices. Indeed, if these gains are low, this provides a simpler explanation of the observed low take-up rate. We did the assessment for several levels of risk aversion, selected following a field experiment in the Cameroonian cotton zone and two utility functions.

To our knowledge, there is no similar work allowing to assess the basis risk of WII for several localities. De Nicola (2011) shows that insurance is able to lead to a large increase in optimal consumption using a dynamic stochastic model calibrated on data from Malawi. Muller et al. (2011) show that fixing the strike of a lump sum insurance contract above 30% lead to in a simulation exercise calibrated on a typical farm in southern Namibia. Both studies however consider only one index which prevents to compare different basis risk levels. They also assume a representative household in a single region with a unique index distribution, limiting the issues of heterogeneous agrometeorological zones we discuss in the third section. De Bock et al. (2010) also study the potential of index insurance for cotton in Mali but the match of annual rainfall and yield data is reduced to 3 districts due to data availability and to only one district because of a lack of correlation between the weather index and yield in the two others. Some other authors look at WII ex ante benefit in different locations (Breustedt, Bokusheva and Heidelbach, 2008; Vedenov and Barnett, 2004 and Berg et al., 2009). Besides studying another crop and location, we assess the basis risk associated with various weather indices.

The next section describes the cotton sector in Cameroon while the third one is dedicated to describing the data and the methods. In the fourth section we present the results before concluding.

2 Cotton sector in Cameroon

2.1 Recent trends

At the peak of production, in 2005, 346 661 farmers cultivated 231 993 ha while, between 2005 and 2010, the number of farmer and the area cultivated with cotton dropped by 40%. Farmers abandoned cotton production after experiencing a dramatic reduction of their margin, mostly due to an increase in fertilizer prices. There are also significant weather-related risks. Cotton is indeed rainfed in almost all sub Saharan African producing countries, and largely depends on rainfall availability. Moreover, farmers who are not able to reimburse their input credit at harvest[1] are not allowed to take a credit during the next year. A situation of unpaid debt would thus be detrimental to those cotton farmers in the long run (Folefack, Kaminski and Enam, 2011). The impact of a potential modification of rainfall distribution during the season or the reduction of its length has been recently found of particular importance (cf. section 3.2) and could even be higher with an increased variability of rainfall (ICAC, 2007 and 2009) that may occur under global warming (Roudier et al., 2011). Lastly, the sector also faces other challenges: an isolation of the North of the country and a decline in soil fertility due to increasing land pressure.

[1] The standing crop is used as collateral and credit reimbursement is deducted from farmers' revenue when the national company purchases the cotton, cf. section 2.2 for further descriptions.

2.2 Purchasing price fixation, current hedging and input credit scheme

In Cameroon, the cotton society (Sodecoton), like its Malian, Senegalese and Chadian counterparts, is still a national monopsony (Delpeuch and Leblois, forthcoming). It is thus the only agent to buy seed cotton from producers at a pan-seasonally and -territorially fixed price, varying marginally depending on cotton quality at harvest. Then, it gins the cotton and sells the fibre on international markets.

As already mentioned by Mayayenda and Hugon (2003), Makdissi and Wodon (2004) and Fontaine and Sindzingre (1991), the price stabilisation has an impact on production decisions since it insures producers against intra-seasonal (and partially against inter-annual) variations of the international cotton price by guaranteeing the announced price.

The cotton sector's institutional setting is also characterized by input provision. Costly inputs are indeed provided on credit by the national companies before sowing, ensuring a minimum input quality and their availability in those remote areas, in spite of a great cash constraint that characterizes the lean season: the so-called 'hunger gap'. Inputs are distributed at sowing (from May 20 and depending on the latitude) and reimbursed at harvest. The amount of credit is deducted, at harvest, from the purchase of the seed cotton.

3 Data and methods

3.1 Area and data

The cotton administration counts 9 regions divided in 38 administrative Sectors. Cotton farmers are grouped into producers' groups (PGs), roughly corresponding to the village level. There are about 2000 active PGs in 2011, which represent an average of about 55 PGs per Sector (the spatial administrative unit used throughout this article).

Yield and gross margin per hectare are provided by the Sodecoton at the Sector level from 1977 to 2010. Agronomic data are matched to a unique meteorological dataset built for this study. It includes daily rainfall and temperatures (minimum, maximum and average) coming from different sources[2], with at least one rainfall station per Sector (Figure 1). Sectors' agronomical data are matched to rainfall data using the nearest station, which is at an average distance of 10 km and a maximum distance of 20 km. Sectors' location are the average GPS coordinates of every Sodecoton's producers group (PG) within the Sector. A Sector represents about 900 square kilometres (cf. Figure 1).

We use ten IRD and Global Historical Climatology Network (GHCN) weather stations of the region: six in Cameroon and four in Chad and Nigeria[3]. Because of the low

[2] *Institut de la Recherche pour le Développement* (IRD) and Sodecoton's high density network of rain gauges.

[3] National Oceanic and Atmospheric Administration (NOAA), available at: www7.ncdc.noaa.gov

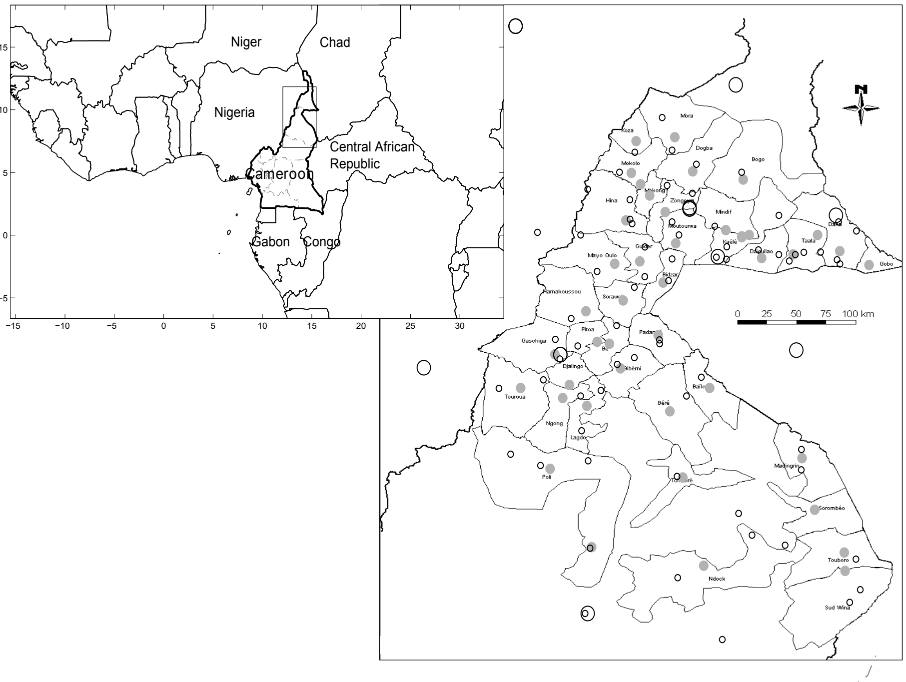

Figure 1: Network of weather stations (large circles) and rainfall stations (small circles) and Sodecoton's administrative zoning: the Sectors level and barycentres of Sectors (grey dots: average of Sectors PGs locations). Sources: Sodecoton, IRD and GHCN (NOAA).

density of the weather stations network, we interpolated, for each Sector, temperature data. We use a simple Inverse Distance Weighting interpolation technique[4], each station being weighted by the inverse of its squared distance to the Sector considered applying a reduction proportional to 6.5 degrees Celsius (°C) per 1000 meters altitude. The average annual cumulative rainfall over the whole producing zone is about 950 millimetres (mm) as showed in Table 1, hiding regional heterogeneities we explore in the next section.

Finally, in addition to rain and temperature data, we use the Normalized Difference Vegetation Index (NDVI), available for a 25 year period spanning from 1981 to 2006 at 8 km spatial resolution which is directly related to green plants biomass[5]. Gross margin observed at the sectoral level is the difference between the value of cotton sold and the value of purchased inputs. We will call it cotton profit (Π) thereafter.

$$\Pi_i = P_t \times Y_i - PC_i \tag{1}$$

i is a year-sector observation, P_t is the annual cotton purchasing price, Y_i is the year-sector yield and PC_i the year-sector costs of inputs, including fertilisers, pesticides, but not labour since the vast majority of workers are self-employed.

[4] IDW method (Shepard 1968), with a power parameter of two.

[5] The NOAA (GIMMS-AVRHH) remote sensing data are available online at: www.glcf.umd.edu/data/gimms), Pinzon et al. (2005).

We restricted the period under consideration for two reasons. First, the profit series suffer from a high attrition rate before 1991, with about one third of missing data (in comparison, only 18% of the data is missing between 1991 and 2010), they are thus strongly unbalanced. Second, the collapse of the cotton sector occurring since 2005 caused large cotton leaks towards Nigeria from that date, also threatening the quality of the data. Moreover, there was a much lower input use after 2005 due to high input prices and in spite of the input credit and significant subsidisation. In the context of high input prices, Sodecoton's inputs misappropriation, for instance to the benefit of food crops, such as maize, is also known to happen very often and could harm profits estimation. We will thus focus on the 1991-2004 sub-period, on which we observe similar summary statistics than on the whole period (Tables 1).

Inter-annual variations in Sodecoton purchasing price and input costs contribute to the variations of cotton profit throughout the period. However we assume out such variations since the inter-annual variations of input and cotton prices are taken into account in crop choice as well as acreage and input use decisions. Hence, estimating the cost of these inter-annual variations would require a model with endogenous crop choice, which is beyond the scope of the present article. We thus value cotton and inputs at their average level over the period considered. By contrast, intra-seasonal prices variations matter, at least those occurring during the crop cycle. We address the issues related to intra-seasonal price variations in section 4.3.

Table 1: Yield and rainfall data summary statistics

Whole period (1977-2010)	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Annual cumulative rainfall (mm per year)	950	227	412	1 790	849
Yield (kg/ha)	1 150	318	352	2 352	849
Cotton profit* (CFA francs per ha)	114 847	50 066	-7 400	294 900	849
1991-2004 sub-period					
Annual cumulative rainfall (mm per year)	953	211	491	1 708	479
Yield (kg/ha)	1 202	297	414	2 117	479
Cotton profit* (CFA francs per ha)	134 323	50 542	4 838	294 900	479

* Profit for one hectare of cotton after input reimbursement, excluding labor.

3.2 Weather and vegetation indices

The role of weather in cotton growing in Western and Central Africa has been documented in previous studies. For instance, Blanc et al. (2008) pointed out the impact of the distribution and schedule of precipitation during the cotton growing season on long run yield plot observations in Mali. The onset and duration of the rainy season were recently found to be the major drivers of year-to-year and spatial variability of yields in the Cameroonian cotton zone (Marteau et al., 2011 and Sultan et al., 2010).

We use the sowing dates reported by the Sodecoton in their reports in the form of the share of the acreage sowed with cotton observed at each of every 10 days, from May 20 to the end of July. We define the beginning of the season as the date for which half of the cotton area is already sown. We also simulate a sowing date following a criterion of the onset of the rainfall season defined by Sivakumar (1988) and adapted to cotton[6]. It is based on the timing of first rainfall daily occurrence and validated on the same data by Bella-Medjo et al. (2009) and Sultan et al. (2010). We tested whether observing the sowing date could be useful to weather insurance compared to using a simulated sowing date. Indeed, simulated sowing date performed well for the same type of insurance contract in the case of millet in Niger, as shown by Leblois et al. (2011). We compared the two growing period schedules, and since we always found the observed one to perform better it is the only one discussed in the article.

Table 2: Indices description.

Index name	Description
CR_{obs} after sowing	Cumulative rainfall (CR) from the observed sowing date to the last rainfall
BCR_{obs} after sowing	CR, capped to 30 mm per day, from the observed sowing date to the last rainfall
$Length_{obs}$ after sowing	Length of the growing cycle, from the observed sowing date to the last rainfall
Sowing $date_{obs}$	Observed sowing date, in days from the first of January

In Table 2, we provide the definition of the four indices retained for their relatively high performance, i.e. indices for which results will be displayed. We first consider the cumulative rainfall (*CR*) over the observed (*obs*) growing period. We then consider a refinement of the cumulative rainfall (referred to as *BCR*), by bounding daily rainfall at 30 mm, corresponding to water that is not used by the crop due to excessive runoff (Baron et al., 2005). We then consider the length of the growing season (*Length*) and the sowing date in days for insuring against a short growing season or a late sowing. In that latter case (sowing date), as opposed to rainfall and season length indices, insurance covers against high values of the index (late sowing).

We have also tested more complicated indices, described in Appendix C.1 and C.2. They are not presented in the results section since they did not perform better than the rather simple indices presented in the results section.

3.3 Definition of rainfall zones

Average annual cumulative rainfall varies between 600 and 1200 mm in the cotton producing area characterized by a Sudano-sahelian climate.

We define five rainfall zones in the following way: we sort Sectors by rainfall level, on the whole period (1991-2004), and regroup them into zones of similar size. The geographical zoning of the cotton cultivation area is displayed in Figure 3 and the distribution of yields, annual cumulative rainfall and length of the rainy season for each zone in Figure 2.

[6] Cotton is sowed later than cereal crops in the Sudano-sahelian zone.

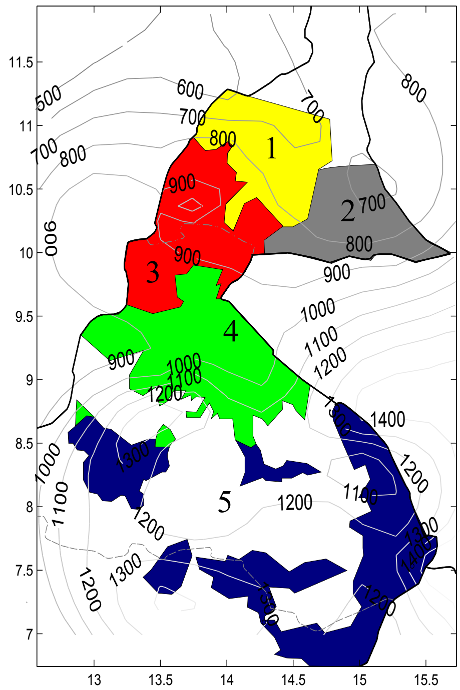

Figure 2: Rainfall zones based on annual cumulative rainfall: North: (1), North East (2), North West (3), Centre (4) and South (5) and isohyets (in mm on the 1970-2010 period). Source: authors calculations.

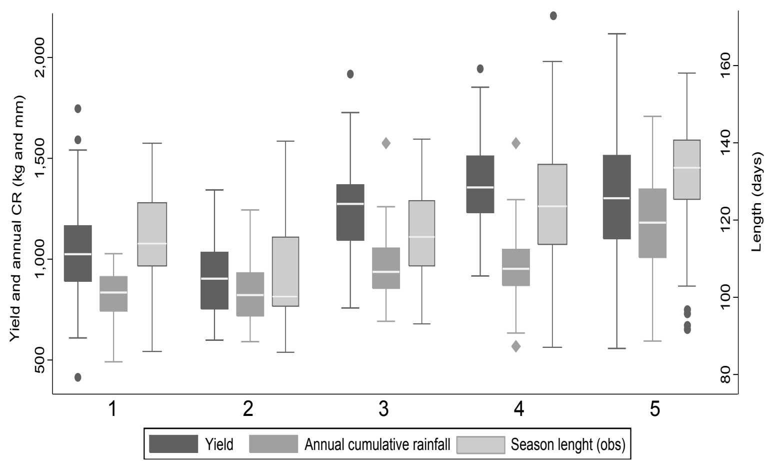

Figure 3: Boxplots of Yield, Annual rainfall and cotton growing season duration in different rainfall zones.

The rainfall zones have different average yield, cumulative rainfall and cotton growing season length. The two northern rainfall zones are sowed (and emerge) 10 to 15 days later; such feature could explain part of the discrepancies among yields, in spite of the development of adapted cultivars for each zone by the agronomic research services.

3.4 Weather index-based insurance set up

The indemnity is a step-wise linear function of the index with 3 parameters: the strike (S), i.e. the threshold triggering indemnity payout; the maximum indemnity (M) and λ, the slope-related parameter. When λ equals one, the indemnity is either M (when the index falls below the strike level) or 0. The strike ideally should correspond to the level at which the meteorological factor becomes limiting. We thus have the following indemnification function depending on x, the weather index realisation (as defined by Vedenov and Barnett, 2004):

$$I(S, M, \lambda, x) = \begin{cases} M, & \text{if } x \leq \lambda.S \\ \frac{S-x}{S\times(1-\lambda)}, & \text{if } \lambda.S < x < S \\ 0, & \text{if } x \geq S \end{cases} \tag{2}$$

We took this functional form because, to our knowledge, almost all index-based insurance, presently implemented or studied ex ante, were based on this precise contract shape. The insurer reimburses the difference between the usual income level and the estimated loss in income coming resulting from a yield loss, yield being proxied by the weather index realisation.

We use different objective functions to maximise farmers' expected utility and show that our results are robust to such a choice. We consider both following objective functions, respectively a constant relative risk aversion (CRRA) utility function (equation 2) and constant absolute risk aversion (CARA) utility function[7] (equation 3). Utility functions are the following:

$$U_{CRRA}(\Pi_i) = \frac{(\Pi_i + w)^{(1-\rho)}}{(1-\rho)} \tag{3}$$

$$U_{CARA}(\Pi_i) = \Big(1 - \exp\big(-\psi \times (\Pi_i + w)\big)\Big) \tag{4}$$

Both objective functions are quite standard in the economic literature. Following Gray et al. (2004), w is the initial wealth, mainly composed of non-cotton production, which calibration is presented in section 3.6.1. ρ and ψ are the risk aversion parameters in each objective function. Risk aversion is equivalent to inequality aversion in this context and we consider the agrometorological relations to be ergodic since we assimilate spatial (Sectoral) variations to time variations.

[7] Results using the CARA objective function are displayed in Appendix B.

The certain equivalent income (CEI) with insurance corresponds to:

$$CEI_{CRRA}(\tilde{\Pi^I}) = \Big((1-\rho) \times EU(\tilde{\Pi^I})\Big)^{\frac{1}{1-\rho}} - w, \qquad \tilde{\Pi^I} = \{\Pi_1^I, ..., \Pi_N^I\} \tag{5}$$

$$CEI_{CARA}(\tilde{\Pi^I}) = (\frac{1}{\psi}) \times log(-EU(\tilde{\Pi^I}) - 1) - w, \qquad \tilde{\Pi^I} = \{\Pi_1^I, ..., \Pi_N^I\} \tag{6}$$

With $EU(\tilde{\Pi})$ the expected utility of the vector of profit realisations ($\tilde{\Pi}$) and N the number of observations. The insured profit (Π^I) is the observed profit (Π_i, as defined in section 3.1) minus the insurance premium plus the hypothetical indemnity:

$$\Pi_i^I = \Pi_i - P(S^*, M^*, \lambda^*) + I_i(S^*, M^*, \lambda^*, x_i) \tag{7}$$

With x_i the year-sector realisation of the weather index. The premium includes the loading factor, β, fixed at 10% of total indemnification, and a transaction cost (C) for each indemnification, fixed exogenously to one percent of the average profit, corresponding to one day of rural wage.

$$P = \frac{1}{N}\Big[(1+\beta) \times \sum_{i=1}^{N} I_i\big(S^*, M^*, \lambda^*, x_i\big) + C \times \sum_{i=1}^{N} F_i\Big], \text{ with } F_i = \begin{cases} 1 \text{ if } I_i > 0 \\ 0 \text{ if } I_i = 0 \end{cases} \tag{8}$$

We finally optimize the three insurance parameters in order to maximise expected utility and look at the gain in CEI depending on the index. The strike is bounded by a maximum indemnification occurrence rate of 25%, corresponding to the insurer's maximum risk loading capacity. These parameters values are consistent with the cost of WII observed in the country with, by far the biggest experience: India (Chetaille et al., 2010).

3.5 Basis risk and certain equivalent income

There is not much theoretical work on the definition of basis risk in the context of index insurance calibration. The Pearson correlation coefficient between weather and yield time series is the only measure used for evaluating the basis risk empirically (see for instance Carter, 2007 and Barnet and Mahul, 2007). Such measure is imperfect because it does not depend on the payout function and the utility function which will determine the capacity of insurance to improve resources allocation.

The basis risk can be considered as the sum of three risks: first, the risk resulting from the index not being a perfect predictor of yield (called index basis risk thereafter). Second, the spatial basis risk: the index may not capture the weather effectively experienced by the farmer (recently put forward by Norton et al., 2012 on US data); all the more so if the farmer is far from the weather station(s) that provide data on which index is calculated. Third, the idiosyncratic basis risk, stemming from heterogeneities among farmers (practices) or among plots (soil conditions). The intra-village yield variation is indeed often found to be high in developing countries, but also in high income countries (Claasen and Just, 2011). The issues arising when dealing with idiosyncratic basis risk in the case of a WII have been previously analysed in Leblois et al. (forthcoming). We will only focus here on the index basis risk.

We propose a tractable definition of the index basis risk, based on the computation of a perfect index that is the observation of the actual cotton profit at the same spatial level (in our case the Sodecoton 'sectors', the lowest administrative unit for which data are available) for which both yield data and weather indices are available.

We thus consider the basis risk (BR) as the difference in percentage of utility gain obtained by smoothing income through time and space lowering the occurrence of bad cotton income through weather index insurance (WII) as compared to a perfect index insurance (PII) with the same contract type. We consider an insurance contract based on yield observed at the Sector level. The contract has the exact same shape (as the payout function defined in section 3.4) and the same hypotheses[8] than the WII contracts, except the index, which is the yield realisation. We will call it PII (perfect index insurance) thereafter, considering this is the best contract possible under those hypotheses.

$$BR = 1 - \frac{CEI(\tilde{\Pi}^I_{WII})}{CEI(\tilde{\Pi}^I_{PII})} \tag{9}$$

3.6 Model calibration

3.6.1 Initial wealth

We use three surveys ran by Sodecoton in order to follow and evaluate farmers' agronomical practices. They respectively cover the 2003-2004, 2006-2007 and 2009-2010 growing seasons. We also use recall data for the 2007 and 2008 growing season from the last survey. The localisations of surveyed clusters (GPs) are distributed across the whole zone, as displayed in Figure 6, in Appendix D. We compute the share of cotton-related income in on-farm income for 5 growing seasons. Cotton is priced at the average annual purchasing price of the Sodecoton and the production of major crops (cotton, traditional and elaborated cultivars of sorghos, groundnut, maize, cowpea) at the price observed in each Sodecoton region.

As showed in Table 3 the share of cotton income represents, in average, 45.5% of the wealth of cotton farmers. Wealth is composed of farm income and farming capital, the latter mainly includes agricultural material and livestock. We thus fix average wealth as the double of average cotton income of our sample. As a robustness check (not shown here), we tested on-farm income as increasing in function of cotton income[9], by estimating

[8] The premium equals the sum of payouts plus 10% of loading factor and a transaction cost.

[9] For two major reasons it can be assumed that cotton yields and other incomes (mainly other crops yields) are correlated. First, even if each crop has its own specific growing period, a good rainy season

Table 3: On-farm and cotton income of cotton producers during the 2003-2010 period (in thousands of CFA francs)

Variable	Mean	Std. Dev.	Min.	Max.	N
Cotton income	246.064	278.751	185	4 525.1	5 190
Wealth*	606.546	661.70	587	9 520.68	5 190
Cotton income share of wealth (%)	**45.5**	23.1	.3	100	5 190

* Composed of farm income and farming capital.
Source: Sodecoton's surveys and author's calculations.

the relation between both variables on the same surveys, but it did not modify the results significantly.

3.6.2 Risk aversion

We led a field work (Nov. and Dec. 2011) to calibrate the risk aversion parameter of the CRRA function, from which the parameters of the CARA utility function can be inferred. Following Lien and Hardaker (2001), we assume that $\psi = \rho/W$, with W the total wealth $(w + E[\Pi])$.

A survey was implemented in 6 Sodecoton groups of producers situated in 6 different locations[10], each in one region, out of the nine administrative regions of the Sodecoton (cf. section 3.1). 15 cotton farmer were randomly selected in each groups, i.e. randomly taken out of an exhaustive list of cotton farmers, which is detained by the Sodecoton operator in each village in order to manage input distribution each year. The core of the survey was designed to evaluate income and technical agronomic practices. Those producers were asked to come back at the end of the survey and lottery games were played in groups of 10 to 15 people. We used a typical Holt and Laury (2002) lottery, apart from the fact that we did not ask for a switching point but to choose 5 times among two lotteries (one risky and one safe) for a given probability of the bad outcome. It thus allowed the respondent to show inconsistent choices, and if not, ensures that she/he understood the framework.

The 5 paired lottery choices played sequentially are displayed in Table 4. At each step the farmers had to choose between a safe (I) and a risky (II) bet, both constituted of two options: a good and a bad harvest. Each option was illustrated by a schematic representation of realistic cotton production in good and bad years. The gains indeed represent the approximate average yield (in kg) for 1/4 of an hectare, the unit historically used by all farmers and Sodecoton for input credit, plot management etc. The gains were displayed in a very simple and schematic way in order to fit potentially low ability of some farmers to read and to understand a chart, given the low average educational attainment in the population. For each lottery game, the choices are associated with different average

for cotton is probably also good for other crops. The same reasoning can be applied to other shocks (e.g. locust invasions). Second, a farmer that has a lot of farming capital is probably able to get better yields in average for all crops.

[10] The localisation of those six villages is displayed in Figure 7 in Appendix D.

Table 4: Lotteries options

Number of BB (prob. of a good outcome)	I RB	I BB	II RB	II BB	Difference (II-I) of expected gains	Risk aversion (CRRA) when switching from I to II
5/10	150	250	50	350	0	≤ 0
6/10	150	250	50	350	20	]0,0.3512]
7/10	150	250	50	350	40	]0.3512,0.7236]
8/10	150	250	50	350	60	]0.7236,1.1643]
9/10	150	250	50	350	80	]1.1643,1.7681]
						> 1.7681

BB goes for black balls and RB for red balls

gains, probabilities were represented by a bucket and ten balls (red for a bad harvest and black for a good harvest). When all participants had made their choice, the realisation of the outcome (good vs. bad harvest) was randomly drawn by children of the village or a voluntary lottery player picking one ball out of the bucket.

The games were played and actual gains were offered at the end. Players were informed, at the beginning of the game that they would earn between 500 and 1500 CFAF francs, 1000 CFAF representing one day of legal minimum wage in Cameroon. We began with the lottery choice associated with equal probabilities, for which the safer option is more interesting. Then, in each game, the relative interest of the risky option increased by raising the probability of a good harvest. We thus can compute the risk aversion level using the switching point from the safe to the risky option (or the absence of switching point).

We drop each respondent that showed an inconsistent choice[11] among the set of independent lottery choices representing 20% of the sample: 16 individuals on 80. We choose the average of each interval extremity as an approximation for ρ, as it is done in the literature (e.g. Yesuf and Bluntstone, 2009).

4 Results

4.1 Risk aversion distribution

Following the methodology presented in section 3.6.2 above, we find that 20% of the sample (N=64) shows a risk aversion below or equal to .72, and 38% a risk aversion superior to 1.77 under CRRA hypothesis. We display the distribution of the individual relative risk aversion of farmers of the 6 villages in Figure 4. Table 15 in Appendix D shows the summary statistics of the obtained parameters in the whole sample and in each village.

[11] For instance a respondent that shows switching points indicating a risk aversion parameter superior to 1.7236 and inferior or equal to .3512 to is dropped.

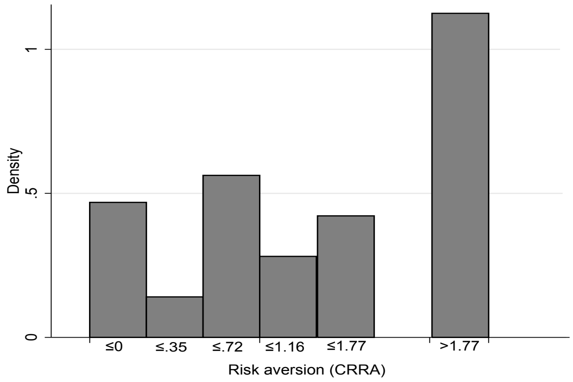

Figure 4: Distribution of relative risk aversion (CRRA) parameter density (N=64).

Given that only the most risk averse agents will subscribe to an insurance (Gollier, 2004) and that 52% of our sample show a risk aversion superior to 1.16, we test a range of values between 1 (the approximate median value) and 3 for the CRRA function ($\rho = [1, 2, 3]$). The parameters of the CARA objective function (cf. section 3.6.2 above) are set in accordance: $\psi = \rho/W$, with W the average wealth: average cotton income plus initial wealth.

4.2 Insurance gains and basis risk

4.2.1 Whole cotton area

The first line of Table 5 shows the gain in percent of CEI that an insurance based on a perfect index would bring, given our assumptions on the payout function presented in section 3.4. The rest of the table shows the gains of other indices as a share of this maximum gain, corresponding to (1-BR). Throughout the paper, we display in bold insurance contract simulations that reach at least 25%, i.e. a basis risk of less than 75%. N.A indicates that the optimisation lead to an absence of insurance, because no gain was found. All results with a CARA utility function are very similar and are displayed in Appendix B.

Table 5: CEI gain of index insurances relative to PII absolute gain from 1991 to 2004.

	CRRA		
	$\rho = 1$	$\rho = 2$	$\rho = 3$
PII CEI **absolute** gain	0.19%	0.92%	1.81%
CEI gains relative to PII			
CR_{obs} after sowing	0%	3.20%	4.22%
BCR_{obs} after sowing	0%	3.20%	5.97%
Length_{obs} after sowing	**26.25%**	**33.66%**	**37.25%**
Sowing date_{obs}	**34.98%**	**50.69%**	**52.46%**

First line of Table 5 shows that the benefit is always low, even for the PII and high risk aversion. Moreover, we observe a very high basis risk exceeding 50% for most indices.

The best performing indices are the length of the growing season and the sowing date itself. This last result is coherent with the existing agronomic literature: Sultan et al. (2010), Blanc et al. (2008) and Marteau et al. (2011) show that the length of the rainy season, and more particularly its onset, are a major determinant of cotton but also cereal yield in the region. It is mostly explained by the fact that the number of bolls (cotton fruit including the fibre and the seeds) and their size are proportional to the cotton tree growth and development, which itself, is proportional to the length of the growing cycle. The better performance of the sowing date compared to the length of the growing period might be explained by the fact that late rains can bring down cotton bolls and thus reduce yield. Hence, comparing two years with the same sowing date, the one with the longest season i.e. with the latest rain may either have higher or lower yield.

As mentioned above, we have tested other indices[12], which all showed lower performance than those presented here. Indeed those indices were more complicated, hence more difficult to understand by potential clients, and did not perform better.

There is a very high subsidisation rate across different regions. In order to show this we divided the cotton zone into 5 rainfall zones (RZ), assuming that they are more homogeneous in terms of weather (the underlying methodology is explained in section 3.3). As shown in Table 6, the driest zones are highly subsidised, while the most humid are highly taxed. Clearly, such an insurance contract would be refused by farmers in the South. Thus, splitting the Malian cotton sector into different zones is required in order to insure yields.

Table 6: Net subsidy rate (in percentage of the sum of premiums paid) of index-based insurances across the 5 rainfall zones (RZ), for rho=2 (CRRA).

	RZ 1	**RZ 2**	**RZ 3**	**RZ 4**	**RZ 5**
CR_{obs} after sowing	4.39%	34.21%	24.05%	-60.97%	-62.57%
BCR_{obs} after sowing	-22.93%	54.15%	37.39%	-49.57%	-83.88%
Length_{obs} after sowing	41.16%	135.27%	-86.02%	-38.43%	-40.94%
Sowing date_{obs}	108.98%	139.31%	-86.20%	-59.49%	-80.57%

Until there, only one insurance contract (characterized by the three parameters: S, λ and M) was considered for the whole Cameroonian cotton zone. We will now calibrate distinct insurance contracts for different homogeneous rainfall zones.

[12] From the simplest to the most complicated: annual cumulative rainfall, the cumulative rainfall over the simulated rainy season (onset and offset set according to Sivakumar, 1988 criterion) and the simulated growing phases (GDD accumulation and cultivars characteristics), the same indices with daily rainfall bounded to 30 mm, the length of the rainy season and the length of the cotton growing season, sum and maximum bi-monthly NDVI values over the rainy season and the NDVI values over October (the end of the season), the cumulative rainfall after cotton plant emergence and the observed duration of the growing season after emergence in days...

4.2.2 Rainfall zoning

Due to cross-subsidisation issues, we divide the Cameroonian cotton zone into five more homogeneous rainfall zones. Table 7 displays, for each index, the in-sample and out-of-sample (in italic) CEI gains with a CRRA utility function when optimizing insurance in each of the rainfall zones[13]. In-sample contract calibrations are displayed in Table 9, Table 10 and Table 11 in Appendix A.

The in-sample gain is the gain of an insurance contract calibrated and tested on the same data. This estimation thus may suffer from over-fitting, which could lead to overestimate insurance gain (Leblois et al., forthcoming). We thus use a leave-one-out technique and consider the gains of an index insurance that would be tested on a different sample that the one on which it is calibrated. For out-of-sample estimates, we calibrate, for each Sector, the insurance contract parameters on the other Sectors of the same rainfall zone. The optimisation constraints about the insurer loading factor does not hold any more on the test sample (but only on the calibration sample). Insurer profits (losses) that are superior (inferior) to the 10% charging rate are equally redistributed to each farmer. This artificially keeps the insurer out-of-sample gain equal to the in-sample case and thus allows comparison with in-sample calibration estimates. However, since out-of-sample estimates allow the insurance contract calibration to be different among different sectors by construction, while in-sample estimates do not, the gains can be a higher in out-of-sample. The interest of out-of-sample estimations appears in particular for the fifth rainfall zone: while BCR_{obs} seem interesting in the insample estimation, it is not the case with the out-of-sample estimation. Since this zone is the most humid, the good result of the insample estimation is probably due to over-fitting.

Looking at optimisations among different rainfall zones leads to a different picture. First, in the third and the fourth rainfall zones, no index can be used to hedge farmers. Both zones are quite specific in terms of agrometeorological conditions. The Mandara mounts, present in the West of the third rainfall zone, are known to stop clouds, explaining such specificity and a relatively high annual cumulative rainfall, with very specific features. The fourth rainfall zone corresponds to the Benue watershed. The Benue is the larger river of the region, contributing to more than half the flow of the Niger River. In both zones, geographic specificities could explain why water availability does not limit yields, in spite of a lower cumulative rainfall in the fifth rainfall zone.

The length of the growing season remains the best performing index. It is the only index that almost systematically leads to positive out-of-sample CEI gain estimations. However, simulation of the sowing date using daily rainfall does not reach comparable results. This result can be interpreted as an evidence of the existence of strong institutional

[13] An alternative would have been to standardise indices by sector i.e. to consider the ratio of the deviation of each observation to the Sector average yield on its standard deviation. Yet, it did not improve significantly the results presumably because the weather index distribution differs across rainfall zones.

Table 7: In-sample and out-of-sample* estimated CEI gain (CRRA) of index insurances relative to PII absolute gain, among different rainfall zones, from 1991 to 2004.

	CRRA		
	$\rho = 1$	$\rho = 2$	$\rho = 3$
First rainfall zone			
PII CEI **absolute** gain	.28%	1.31%	2.57%
	.25%	*1.30%*	*2.40%*
CR$_{obs}$ after sowing	0%	0%	1.34%
	0%	*-.31%*	*-.52%*
BCR$_{obs}$ after sowing	0%	7.36%	13.75%
	0%	*-18.76%*	*-28.66%*
Length$_{obs}$ after sowing	6.52%	24.47%	**34.76%**
	-40.67%	***37.10%***	*24.72%*
Sowing date$_{obs}$	0%	**37.58%**	**45.64%**
	49.82%	***97.74%***	***91.68%***
Second rainfall zone			
PII CEI **absolute** gain	.05%	.67%	1.54%
	.05%	*.63%*	*1.43%*
CR$_{obs}$ after sowing	0%	0%	8.64%
	0%	*.19%*	*.67%*
BCR$_{obs}$ after sowing	0%	0%	9.89%
	0%	*-33.13%*	*9.28%*
Length$_{obs}$ after sowing	0%	20.22%	24.85%
	0%	***39.96%***	***49.90%***
Sowing date$_{obs}$	0%	**44.86%**	**54.61%**
	0%	***48.72%***	***69.06%***
Third rainfall zone			
PII CEI **absolute** gain	.15%	.99%	2.00%
	.18%	*.99%*	*2.06%*
CR$_{obs}$ after sowing	0%	4.81%	4.85%
	0%	*0%*	*0%*
BCR$_{obs}$ after sowing	0%	4.81%	4.85%
	0%	*0%*	*0%*
Length$_{obs}$ after sowing	0%	0%	.89%
	0%	*-178.99%*	*-147.85%*
Sowing date$_{obs}$	0%	0%	0%
	-410.55%	*-216.22%*	*-158.67%*
Fourth rainfall zone			
PII CEI **absolute** gain	.51%	.95%	1.96%
	.09%	*.71%*	*1.54%*
CR$_{obs}$ after sowing	0%	0%	1.30%
	0%	*-.06%*	*-.01%*
BCR$_{obs}$ after sowing	0%	0%	1.30%
	0%	*-8.89%*	*-3.62%*
Length$_{obs}$ after sowing	0%	0%	0%
	0%	*0%*	*0%*
Sowing date$_{obs}$	0%	0%	0%
	0%	*0%*	*0%*
Fifth rainfall zone			
PII CEI **absolute** gain	.20%	1.49%	2.35%
	.10%	*.75%*	*1.59%*
CR$_{obs}$ after sowing	0%	24.15%	**27.79%**
	-.37%	*-.10%*	*-.37%*
BCR$_{obs}$ after sowing	**51.56%**	**47.41%**	**44.69%**
	-133.34%	*-108.54%*	*-23.07%*
Length$_{obs}$ after sowing	**57.45%**	**46.60%**	**44.71%**
	183.27%	*-25.54%*	***48.40%***
Sowing date$_{obs}$	**69.48%**	**49.91%**	**46.82%**
	-147.51%	*-10.80%*	***78.99%***

* Leave-one-out estimations are displayed in italic

constraints explaining late sowing such as the existence of institutional delays. Delays in seed and input delivery, as mentioned by Kaminsky et al. (2011), indeed could explain some late sowing and thus the low performance of indices that are only based on daily rainfall observations and not on the observed sowing date. Alternatively, the Sivakumar criterion for simulating the onset of the rainy season may not suit cotton as well as cereals. However, there is no other criterion for simulating cotton sowing date to our knowledge.

In other contexts, using the actual sowing date in an insurance contract is difficult because it cannot be observed costlessly by the insurer. However, in the case of cotton in French speaking West Africa, cotton production mainly relies on interlinking input-credit schemes taking place before sowing and obliging the cotton company to follow production in each production group. As mentioned by De Bock et al. (2010), cotton national monopsonies (i.e. Mali in their case and Cameroon in ours) already gather information about the sowing date in each region. The sowing date would thus be available at no cost to the department of production at Sodecoton. Under those circumstances observing the sowing date, making it transparent and free of any distortion and including it in an insurance contract would not be so costly.

There are also potential moral hazard and agency issues when insuring against a declared sowing date. However, in our case, the sowing date is aggregated at the Sector level (about 55 GP each representing about 4 000 producers). This means that a producer, and even a coordination of producer within a GP, is not able to influence the average sowing date at the Sector level by declaring a late date or by sowing, on purpose, later than optimally.

4.3 Implicit intra-seasonal price insurance

As mentioned earlier (in section 2.2), as Sodecoton announces harvest price before sowing, the firm insures farmers against intra-seasonal variations of the international price. Furthermore, looking at the variation of Sectoral yields and intra-seasonal international cotton price variations during the 1991-2004 period, the latter vary twice as much as the former (coefficient of variation of 0.28 for yield vs. 0.42 for intra-seasonal international cotton price). Admittedly, this is obtained by considering the 1993-1994 season during which the CFAF value was halved. However, the sample without this very specific year still shows a slightly higher coefficient of variation than yield (0.32 vs. 0.28)[14].

Sodecoton possibly offers such implicit price insurance at a cost, it is however very difficult to compute such cost. We will thus consider, both for yield and for intra-seasonal price that it is a free insurance mechanism (we thus call it stabilisation). This does not affect the argument that the level of the price risk is significant, especially relatively to other risks.

[14] This also holds when considering the 1977-2010 period, and when dropping 1993-1994 and 2010 specific years (during which the peak cotton price has been observed).

Table 8: CEI gain of intra-seasonal price and yield stabilisation (in-sample parameter calibration) in each rainfall zone (RZ) and in the whole cotton zone (CZ)

		RZ1	RZ2	RZ3	RZ4	RZ5	**CZ**
(1)	CEI gain of intra-seasonal price stab. (CRRA, ρ=2)	10.28%	11.33%	11.84%	12.85%	17.85%	12.98%
(2)	CEI gain of intra-seasonal price stab. (CARA, ψ=2/W)	5.41%	4.96%	6.66%	7.23%	8.84%	6.72%
(3)	CEI gain of yield stab. (CRRA, ρ=2)	3.09%	.74%	2.88%	1.91%	3.75%	2.46%
(4)	CEI gain of yield stab. (CARA, ψ=2/W)	1.49%	.40%	1.07%	1.00%	1.77%	1.16%
(3)/(1)		3.33	15.31	4.11	6.73	4.76	5.28
(4)/(2)		3.63	12.40	6.22	7.23	4.99	5.79

We compute the relative variation between the average prices during the 4 months period after harvest and compared it to the 4 month period before sowing. This coefficient allows us to simulate the profit variations resulting from intra-seasonal price variations by attributing this variation on the observed producer price and to compute the gain in term of CEI of the implicit insurance offered by the cotton company. Table 8 shows the gain due to the stabilisation of intra-seasonal cotton price variations (considering the international price at harvest to the one at sowing) and the gain of a stabilisation of Sectoral yield levels (fixed to the average Sectoral yield) with the observed yield distribution in each rainfall zone. The last column of Table 8 shows the CEI gain brought by the stabilisation of intra-seasonal cotton international price and yields for the whole cotton zone on the same period. The stabilisation of yield brings a much lower gain than the stabilisation of intra-seasonal variation of international cotton price which are already hedged: depending on the rainfall zone, the gain from the former is between 3 and 15 times that of the latter.

5 Conclusion

Micro-insurance, and in particular weather-index insurance, is currently strongly supported by development agencies and financial institutions, in particular the World Bank (2012). In this paper, we provide an ex ante assessment of weather-index insurance for risk-averse cotton farmers in Cameroon. We compute the benefit of such insurance for several weather indices, three levels of risk aversion (whose distribution was assessed through a field work) and two different utility functions. To avoid over-fitting, we use an out-of-sample estimation technique.

Our results invite to be cautious about the benefits of weather-index insurance. Firstly, even if the weather index were a perfect predictor of cotton yield (which is impossible), the benefit for farmers in term of certain equivalent income would be lower than 3%. This is much less than the benefit of the hedging against intra-annual price fluctuations currently provided by the national cotton company. While promoting weather-index insurance, international institutions that pushed for market liberalisation in the cotton sector (Leblois and Delpeuch, forthcoming), probably should also recommend price stabilization schemes, for instance using option systems hedging against international price risk within contract farming schemes.

Moreover, we show that all weather indices are highly imperfect. In two out of the five rainfall zones which we have defined for this study, no weather index is able to provide a benefit to farmers. In the remaining three rainfall zones, even the best indices present a basis risk of about one half, i.e. they would provide only half of the (already low) benefit of a hypothetical perfect index.

On a more positive note, we conclude that the best indices are very simple, hence could be easily understood by farmers. Furthermore, these indices (the length of the rainy season and the sowing date) are consistent with the agronomic literature, which concludes that they are better predictors of cotton yields than e.g. cumulated rainfall. Moreover, national cotton companies could distribute such insurance products at a relatively low cost since they already sell inputs credits to, and buy cotton from, all cotton producers. All in all, while providing hedging products to small-scale farmers in low-income countries is certainly welcome, due care should be given to the quantification of the different risks these farmers face and to the institutions which could provide, or already provide, these hedging products.

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References

Anyamba, A., and C. Tucker (2012): *Historical Perspectives on AVHRR NDVI and Vegetation Drought Monitoring.* In: Remote Sensing of Drought: Innovative Monitoring Approaches; Brian, D . Wardlow, Martha C . Anderson, and James P . Verdin.

Baron, C., B. Sultan, B. Maud, B. Sarr, S. Traore, T. Lebel, S. Janicot, and M. Dingkuhn (2005): "From GCM grid cell to agricultural plot: scale issues affecting modelling of climate impact," *Phil. Trans. R. Soc.*, 360, 2095–2108.

Bella-Medjo (Tsogo), M. (2009): "Analyse multi-échelle de la variabilité pluviométrique au cameroun et ses conséquences sur le rendement du coton," Ph.D. thesis, Université Pierre et Marie Curie.

Berg, A., P. Quirion, and B. Sultan (2009): "Can weather index drought insurance benefit to Least Developed Countries' farmers? A case study on Burkina Faso," *Weather, Climate and Society*, 1, 7184.

Blanc, E., P. Quirion, and E. Strobl (2008): "The climatic determinants of cotton yields: Evidence from a plot in West Africa," *Agricultural and Forest Meteorology*, 148(6-7), 1093 – 1100.

Breustedt, G., R. Bokusheva, and O. Heidelbach (2008): "Evaluating the Potential of Index Insurance Schemes to Reduce Crop Yield Risk in an Arid Region," *Journal of Agricultural Economics*, 59(2), 312–328.

Bryan, G. (2012): "Social Networks and the Decision to Insure: Evidence from Randomized Experiments in China," Discussion paper, University of California Berkeley, mimeo.

Cai, J., A. D. Janvry, and E. Sadoulet (2012): "Social Networks and the Decision to Insure," Discussion paper, Berkeley University, mimeo.

Chetaille, A., A. Duffau, D. Lagandré, G. Horréard, B. Oggeri, and I. Rozenkopf (2010): "Gestion de risques agricoles par les petits producteurs, focus sur l'assurance-récolte indicielle et le warrantage," Discussion paper, GRET.

Claassen, R., and R. E. Just (2011): "Heterogeneity and Distributional Form of Farm-Level Yields," *American Journal of Agricultural Economics*, 93(1), 144–160.

Cole, S., X. Gin, J. Tobacman, P. Topalova, R. Townsend, and J. Vickrey (forthcoming): "Barriers to Household Management: Evidence from India," *American Economic Journal: Applied Economics.*

Crétenet, M., and D. Dessauw (2006): "Production de coton-graine de qualité, guide technique No.1," Discussion paper, CIRAD.

De Bock, O., M. Carter, C. Guirkinger, and R. Laajaj (2010): "Étude de faisabilité: Quels mécanismes de micro-assurance privilégier pour les producteurs de coton au Mali ?," Discussion paper, Centre de Recherche en Economie du Développement, FUNDP - Département de sciences économiques.

de Nicola, F. (2011): "The Impact of Weather Insurance on Consumption, Investment, and Welfare," 2011 Meeting Papers 548, Society for Economic Dynamics.

Delpeuch, C., and A. Leblois (Forthcoming): "Sub-Saharan African cotton policies in retrospect," *Development Policy Review.*

Dessauw, D., and B. Hau (2008): "Cotton breeding in French-speaking Africa: Milestones and prospectss," in *Invited paper for the Plant Breeding and Genetics research topic.*

Folefack, D. P., J. Kaminski, and J. Enam (2011): "Note sur le contexte historique et gestion de la filière cotonnière au Cameroun," Discussion paper, mimeo.

Fontaine, J. M., and A. Sindzingre (1991): "Structural Adjustment and Fertilizer Policy in Sub-Saharan Africa," Discussion paper, OECD.

Freeland, J. T. B., B. Pettigrew, P. Thaxton, and G. L. Andrews (2006): "Chapter 13A in guide to agricultural meteorological practices," in *Agrometeorology and cotton production*.

Giné, X., D. Karlan, and M. Ngatia (2012): "Social networks, financial literacy and index insurance," Discussion paper, Yale.

Giné, X., and D. Yang (2009): "Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi," *Journal of Development Economics*, 89, 1–11.

Gollier, C. (2004): *The Economics of Risk and Time*, vol. 1. The MIT Press, 1 edn.

Gray, A. W., M. D. Boehlje, B. A. Gloy, and S. P. Slinsky (2004): "How U.S. Farm Programs and Crop Revenue Insurance Affect Returns to Farm Land," *Applied Economic Perspectives and Policy*, 26(2), 238–253.

Hayes, M., and W. Decker (1996): "Using NOAA AVHRR data to estimate maize production in the United States Corn Belt," *International Journal of Remote Sensing*, 17, 3189–3200.

Hill, R. V., J. Hoddinott, and N. Kumar (2011): "Adoption of weather index insurance: Learning from willingness to pay among a panel of households in rural Ethiopia," IFPRI discussion papers 1088, International Food Policy Research Institute (IFPRI).

Holt, C. A., and S. K. Laury (2002): "Risk Aversion and Incentive Effects," *American Economic Review*, 92, 1644–1655.

International Cotton Advisory Committee (ICAC) (2007): "Global warming and cotton production Part 1," Discussion paper.

——— (2009): "Global warming and cotton production Part 2," Discussion paper.

Kaminski, J., J. Enam, and D. P. Folefack (2011): "Hétérogénéité de la performance contractuelle dans une filière intégre : cas de la filière cotonnière camerounaise," Discussion paper, mimeo.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2012): "Agricultural Decisions after Relaxing Credit and Risk Constraints," Discussion paper, Yale University, mimeo.

Leblois, A., P. Quirion, A. Alhassane, and S. Traoré (forthcoming): "Weather index drought insurance: an ex ante evaluation for millet growers in Niger," *Environmental and Resource Economics*.

Levrat, R. (2010): *Culture commerciale et développement rural l'exemple du coton au Nord-Cameroun depuis 1950*. L'Harmattan.

Lien, G., and J. Hardaker (2001): "Whole-farm planning under uncertainty: impacts of subsidy scheme and utility function on portfolio choice in Norwegian agriculture," *European Review of Agricultural Economics*, 28(1), 17–36.

Makdissi, P., and Q. Wodon (2004): "Price Liberalization and Farmer Welfare Under Risk Aversion: Cotton in Benin and Ivory Coast," Cahiers de recherche 04-09, Département d'Economie de la Faculte d'administration l'Universite de Sherbrooke.

Marteau, R., B. Sultan, V. Moron, A. Alhassane, C. Baron, and S. B. Traoré (2011): "The onset of the rainy season and farmers sowing strategy for pearl millet cultivation in Southwest Niger," *Agricultural and Forest Meteorology*, 151(10), 1356 – 1369.

Maselli, F., C. Conese, L. Petkov, and M. Gialabert (1993): "Environmental monitoring and crop forecasting in the Sahel trought the use of NOAA NDVI data. A case study: Niger 1986-89," *International Journal of Remote Sensing*, 14, 3471–3487.

Mayeyenda, A., and P. Hugon (2003): "Les effets des politiques des prix dans les filières coton en Afrique zone franc: analyse empirique," *Économie rurale*, 275(1), 66–82.

McLaurin, M. K., and C. G. Turvey (2012): "Applicability of the Normalized Difference Vegetation Index (NDVI) in Index-Based Crop Insurance Design," *Weather Climate and Society*, pp. 271–284.

Meroni, M., and M. Brown (2012): "Remote sensing for vegetation monitroing: potential applications for index insurance," Ispra. JRC, ftp://mars.jrc.ec.europa.eu/index-insurance-meeting/presentations/7_meroni_brown.pdf.

Mobarak, A. M., and M. R. Rosenzweig (2012): "Selling Formal Insurance to the Informally Insured," Discussion paper, Yale Economics Department Working Paper No. 97.

Muller, B., M. F. Quaas, K. Frank, and S. Baumgrtner (2011): "Pitfalls and potential of institutional change: Rain-index insurance and the sustainability of rangeland management," *Ecological Economics*, 70(11), 2137 – 2144, Special Section - Earth System Governance: Accountability and Legitimacy.

Norton, M. T., C. G. Turvey, and D. E. Osgood (2012): "Quantifying Spatial Basis Risk for Weather Index Insurance," *The Journal of Risk Finance*, 14, 20–34.

Pinzon, J., M. Brown, and C. Tucker (2005): *Satellite time series correction of orbital drift artifacts using empirical mode decomposition.* In: N. Huang (Editor), Hilbert-Huang Transform: Introduction and Applications.

Roudier, P., B. Sultan, P. Quirion, and A. Berg (2011): "The impact of future climate change on West African crop yields: What does the recent literature say?," *Global Environmental Change*, 21(3), 1073 – 1083.

Shepard, D. (1968): "A two-dimensional interpolation function for irregularly-spaced data," in *Proceedings of the 1968 23rd ACM national conference*, ACM '68, pp. 517–524, New York, NY, USA. ACM.

Sivakumar, M. V. K. (1988): "Predicting rainy season potential from the onset of rains in Southern Sahelian and Sudanian climatic zones of West Africa," *Agricultural and Forest Meteorology*, 42(4), 295 – 305.

Sultan, B., M. Bella-Medjo, A. Berg, P. Quirion, and S. Janicot (2010): "Multi-scales and multi-sites analyses of the role of rainfall in cotton yields in West Africa," *International Journal of Climatology*, 30, 58–71.

The World bank (2012): "Africa can help feed Africa, Removing Barrier to Regional Trade in Food Staples," Discussion paper, The World Bank.

Vedenov, D. V., and B. J. Barnett (2004): "Efficiency of Weather Derivates as Primary Crop Insurance Instruments," *Journal of Agricultural and Resource Economics*, 29(3), 387–403.

Yesuf, M., and R. A. Bluffstone (2009): "Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia," *American Journal of Agricultural Economics*, 91(4), 1022–1037.

A In-sample contract parameter calibration

Table 9: Indemnification rate in in-sample calibrations (CRRA), among different rainfall zones, from 1991 to 2004.

	CRRA		
	$\rho = 1$	$\rho = 2$	$\rho = 3$
First rainfall zone			
PII	14.29%	25.00%	25.00%
CR_{obs} after sowing	.00%	.00%	17.07%
BCR_{obs} after sowing	.00%	4.88%	4.88%
$Length_{obs}$ after sowing	7.32%	24.39%	24.39%
Sowing $date_{obs}$	.00%	21.95%	21.95%
Second rainfall zone			
PII	11.25%	25.00%	25.00%
CR_{obs} after sowing	.00%	2.44%	21.95%
BCR_{obs} after sowing	.00%	9.76%	24.39%
$Length_{obs}$ after sowing	.00%	12.20%	24.39%
Sowing $date_{obs}$	.00%	24.39%	24.39%
Third rainfall zone			
PII	17.65%	22.35%	24.71%
CR_{obs} after sowing	2.04%	2.04%	2.04%
BCR_{obs} after sowing	2.04%	2.04%	2.04%
$Length_{obs}$ after sowing	.00%	.00%	4.08%
Sowing $date_{obs}$	.00%	.00%	.00%
Fourth rainfall zone			
PII	17.60%	24.80%	24.80%
CR_{obs} after sowing	.00%	.00%	10.14%
BCR_{obs} after sowing	.00%	.00%	10.14%
$Length_{obs}$ after sowing	.00%	.00%	.00%
Sowing $date_{obs}$	.00%	.00%	.00%
Fifth rainfall zone			
PII	3.81%	24.76%	24.76%
CR_{obs} after sowing	4.26%	12.77%	12.77%
BCR_{obs} after sowing	10.64%	10.64%	10.64%
$Length_{obs}$ after sowing	4.26%	14.89%	14.89%
Sowing $date_{obs}$	4.26%	12.77%	12.77%

Table 10: Slope related parameter (λ) in in-sample calibrations (CRRA), among different rainfall zones, from 1991 to 2004.

	CRRA		
	$\rho = 1$	$\rho = 2$	$\rho = 3$
First rainfall zone			
PII	64.29%	64.29%	64.29%
CR_{obs} after sowing	.00%	.00%	100.00%
BCR_{obs} after sowing	.00%	100.00%	100.00%
$Length_{obs}$ after sowing	100.00%	100.00%	100.00%
Sowing $date_{obs}$	.00%	7.14%	64.29%
Second rainfall zone			
PII	100.00%	100.00%	100.00%
CR_{obs} after sowing	.00%	28.57%	100.00%
BCR_{obs} after sowing	.00%	92.86%	100.00%
$Length_{obs}$ after sowing	.00%	100.00%	92.86%
Sowing $date_{obs}$	.00%	57.14%	57.14%
Third rainfall zone			
PII	14.29%	92.86%	92.86%
CR_{obs} after sowing	57.14%	64.29%	85.71%
BCR_{obs} after sowing	64.29%	64.29%	42.86%
$Length_{obs}$ after sowing	.00%	.00%	100.00%
Sowing $date_{obs}$	.00%	.00%	.00%
Fourth rainfall zone			
PII	92.86%	92.86%	92.86%
CR_{obs} after sowing	.00%	.00%	100.00%
BCR_{obs} after sowing	.00%	.00%	100.00%
$Length_{obs}$ after sowing	.00%	.00%	.00%
Sowing $date_{obs}$	.00%	.00%	.00%
Fifth rainfall zone			
PII	71.43%	100.00%	100.00%
CR_{obs} after sowing	100.00%	92.86%	92.86%
BCR_{obs} after sowing	100.00%	100.00%	100.00%
$Length_{obs}$ after sowing	100.00%	14.29%	50.00%
Sowing $date_{obs}$	7.14%	.00%	42.86%

Table 11: Maximum indemnification (M, in CFA francs) in in-sample calibrations (CRRA), among different rainfall zones, from 1991 to 2004.

	CRRA		
	$\rho = 1$	$\rho = 2$	$\rho = 3$
First rainfall zone			
PII	74905	84268	93631
CR_{obs} after sowing	0	0	13566
BCR_{obs} after sowing	0	27131	36175
$Length_{obs}$ after sowing	22609	27131	31653
Sowing $date_{obs}$	0	76872	85915
Second rainfall zone			
PII	22002	29336	33003
CR_{obs} after sowing	0	35016	11672
BCR_{obs} after sowing	0	11672	11672
$Length_{obs}$ after sowing	0	19453	19453
Sowing $date_{obs}$	0	19453	23344
Third rainfall zone			
PII	129991	39997	44997
CR_{obs} after sowing	106553	135613	82336
BCR_{obs} after sowing	101710	130770	145300
$Length_{obs}$ after sowing	0	0	14530
Sowing $date_{obs}$	0	0	0
Fourth rainfall zone			
PII	35852	46095	51216
CR_{obs} after sowing	0	0	10087
BCR_{obs} after sowing	0	0	10087
$Length_{obs}$ after sowing	0	0	0
Sowing $date_{obs}$	0	0	10087
Fifth rainfall zone			
PII	47279	33095	37823
CR_{obs} after sowing	19980	24975	29971
BCR_{obs} after sowing	29971	39961	39961
$Length_{obs}$ after sowing	39961	154848	94907
Sowing $date_{obs}$	109892	84916	54946

B Robustness to the objective function choice: results with CARA

Table 12: CEI gain of index insurances relative to PII absolute gain from 1991 to 2004.

	CARA		
	$\psi = 1/W$	$\psi = 2/W$	$\psi = 3/W$
PII CEI **absolute** gain	.40%	1.16%	1.88%
CEI gains relative to PII			
CR_{obs} after sowing	3.29%	4.94%	7.58%
0%	.56%		
BCR_{obs} after sowing	3.29%	6.94%	10.19%
Length_{obs} after sowing	**32.04**%	**36.79**%	**39.95**%
Sowing date_{obs}	**46.43**%	**49.81**%	**52.49**%

The first result is that the ranking among different indices performance is not modified when considering a different utility function. Second, the relative value of PII to WII (or the relative level of basis risk) also remains unchanged.

Table 13: In-sample and out-of-sample* estimated CEI gain (CARA) of index insurances relative to PII absolute gain, among different rainfall zones, from 1991 to 2004.

	CARA		
	$\psi = 1/W$	$\psi = 2/W$	$\psi = 3/W$
First rainfall zone			
PII CEI **absolute** gain	.11%	.56%	1.09%
	.10%	*.57%*	*1.10%*
CR_{obs} after sowing	0%	0%	0%
	0%	*-.09%*	*-.26%*
BCR_{obs} after sowing	0%	0%	7.03%
	0%	*0%*	*-21.59%*
$Length_{obs}$ after sowing	0%	19.66%	**30.32%**
	-47.22%	*-23.25%*	*1.61%*
Sowing $date_{obs}$	0%	**33.89%**	**42.29%**
	-15.84%	***32.68%***	***43.58%***
Second rainfall zone			
PII CEI **absolute** gain	0%	.19%	.48%
	0%	*.17%*	*.44%*
CR_{obs} after sowing	0%	0%	8.02%
	0%	*.08%*	*.27%*
BCR_{obs} after sowing	0%	0%	9.85%
	0%	*-115.47%*	*-14.66%*
$Length_{obs}$ after sowing	0%	18.27%	**25.36%**
	0%	*9.20%*	*9.08%*
Sowing $date_{obs}$	0%	**39.23%**	**55.52%**
	0%	*14.52%*	*-56.34%*
Third rainfall zone			
PII CEI **absolute** gain	.05%	.38%	.79%
	.04%	*.22%*	*.55%*
CR_{obs} after sowing	0%	5.32%	5.33%
	0%	*0%*	*-.03%*
BCR_{obs} after sowing	0%	5.32%	5.33%
	0%	*0%*	*0%*
$Length_{obs}$ after sowing	0%	0%	1.17%
	0%	*-223.85%*	*-117.81%*
Sowing $date_{obs}$	0%	0%	0%
	1748.96%	*-357.76%*	*-158.65%*
Fourth rainfall zone			
PII CEI **absolute** gain	.08%	.51%	1%
	.07%	*.49%*	*.98%*
CR_{obs} after sowing	0%	0%	2.03%
	0%	*-.03%*	*0%*
BCR_{obs} after sowing	0%	0%	2.03%
	0%	*-10.74%*	*-5.46%*
$Length_{obs}$ after sowing	0%	0%	0%
	0%	*0%*	*0%*
Sowing $date_{obs}$	0%	0%	0%
	0%	*0%*	*0%*
Fifth rainfall zone sample			
PII CEI **absolute** gain	.04%	.30%	.65%
	.10%	*.19%*	*.50%*
CR_{obs} after sowing	0%	20.92%	**25.12%**
	-.09%	*-.03%*	*-.16%*
BCR_{obs} after sowing	48.97%	**46.01%**	**43.39%**
	82.51%	*-83.17%*	*-41.19%*
$Length_{obs}$ after sowing	**55.11%**	**45.03%**	**44.03%**
	66.24%	***28.24%***	***43.22%***
Sowing $date_{obs}$	**66.54%**	**48.45%**	**45.75%**
	44.18%	***92.74%***	***68.33%***

* Leave-one-out estimations are displayed in italic

C Additional indices tested, rainfall zones definition and insurance gains

C.1 Growing period and growing phases schedule

As mentioned in section 3.2, we compared simulated sowing date with the observed ones for each of the indices mentioned. We also try to distinguish different growing phases of the cotton crop. Cutting-in growing phases allows to determine a specific trigger for indemnifications in each growing phase. We do that by defining emergence, which occurs when reaching an accumulation of 15 mm of rain and 35 growing degree days (GDD)[15] after the sowing date. We then set the length of each of the 5 growing phases following emergence only according to the accumulation of GDD, as defined by Crétenet and Dessauw (2006) and Freeland et al. (2006). The end of each growing phases are triggered by the following thresholds of degree days accumulation after emergence: first square (400), first flower (850), first open boll (1350) and harvest (1600). The first phase begins with emergence and ends with the first square, the second ends with the first flower. The first and second phases are the vegetative phases, the third phase is the flowering phase (reproductive phase), the fourth is the opening of the bolls, the fifth is the maturation phase that ends with harvest.

The use of different cultivars, adapted to the specificity of the climate (with much shorter growing cycle in the drier areas) requires to make a distinction different seasonal schedule across time and space. For instance, recently, the IRMA D 742 and BLT-PF cultivars were replaced in 2007 by the L 484 cultivar in the Extreme North and IRMA A 1239 by the L 457 in 2008 in the North province. We simulated dates of harvest and critical growing phases[16] using Dessauw and Hau (2002) and Levrat (2010). The beginning and end of each phase were constraint to fit each cultivar's growing cycle, Table 14 in Appendix C.1 review the schedule of critical growing phases for each cultivar.

The total need is 1600 GDD, corresponding to about an average of 120 days in the considered producing zone, the length of the cropping season thus seem to be a limiting factor, especially in the upper zones (Figure 2) given that an average of 150 needed for regular cotton cultivars, Crétenet et al. (2006).

C.2 Remote sensing indicators

According to Anyamba and Tucker (2012), MODIS derived products, such as NDVI, can not directly be used for drought monitoring or insurance since it requires huge delays in data processing, homogenisation from difference satellites data source and validation from research scientists. However, they underline the existence of very similar near real-time

[15] Calculated upon a base temperature of 13 °C.

[16] See Figure 5 in Appendix C.1 for the spatial distribution of cultivars.

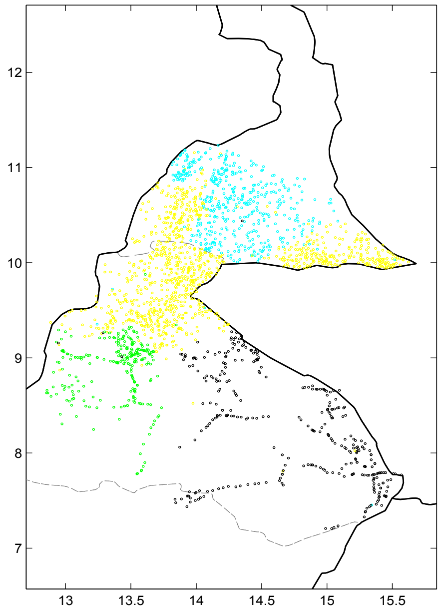

Figure 5: Spatial repartition of cultivars in 2010, dots are representing producers groups buying seeds, IRMA 1239 in black, IRMA A 1239 in green, IRMA BLT-PF in yellow and IRMA D742 in cyan.

Table 14: Cotton cultivars average spatial and temporal allocation

Cultivars *(by province)*	1^{st} **flower date** (Days after emergence)	1^{st} **boll date** (Days after emergence)	**Period of use**
Allen commun	61	114	untill 1976
444-2			untill 1976
Allen 333	59	111	1959-197?
BJA 592	61	114	1965-197?
IRCO 5028	61	111	untill 1987
IRMA 1243	53	102	1987 - 1998
IRMA 1239	52	101	2000-2007
IRMA A 1239	52	101	2000-2007
L 457	52	104	2008-onwards
Extrême-Nord			
IRMA L 142-9	59	109	until 1984
IRMA 96+97	55	115	1985 - 1991
IRMA BLT	51	99	1999-2002
IRMA BLT-PF	56	116	2000 - 2006
IRMA D 742	51	95	2003-2006
IRMA L 484	51	105	2007 - onwards

Sources: Dessauw (2008) and Levrat (2010).

(less than 3 hours from observation) products, such as eMODIS from USGS EROS used for drought monitoring by FEWS.

There is also a cost in terms of transparency to use such complex vegetation index that is not directly understandable for smallholders. There is thus a trade-off to be made between delays (minimized when using near real-time products), transparency and basis risk. In a similar study in Mali (De Bock et al., 2010) vegetation index is found to be more precise than rainfall indices following a criterion of basis risk (defined as the correlation between yield and the index).

We used the bi-monthly satellite imagery (above-mentioned NDVI) during the growing season: and considered annual series from the beginning of April to the end of October. We standardized the series, for dropping topographic and soil specificities, following Hayes and Decker (1996) and Maselli et al. (1993) in the case of the Sahel. There is 2 major ways of using NDVI: one can alternatively consider the maximum value or the sum of the periodical observation of the indicator (that is already a sum of hourly or daily data) for a given period (say the GS). As an example Meroni and Brown (2012) proxied biomass production by computing an integral of remote sensing indicators (in that particular case: FAPAR) during the growing period. Alternatively considering the maximum over the period is also possible since biomass (and thus dry weight) is not growing linearly with photosynthesis activity during the cropping season, but grows more rapidly when NDVI is high. McLaurin and Turvey (2011) for instance considers, in the case of index insurance, that the maximum represents the best vegetal cover attained during the GS and will better proxy yields. We thus tested indices using both methods and also considered all bi-monthly observations of standardized NDVI during the cotton cropping season.

D Income surveys and risk aversion assessment experiment

Table 15: Risk aversion summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
ρ	1.635	1.181	0	3	64
Among which:					
ρ (Dogba)	1.35	0.539	.176	1.466	10
ρ (Mo'o)	1.796	1.302	0	3	10
ρ (Djarengol-Kodek)	1.897	1.199	0	3	11
ρ (Bidzar)	2	1.5	0	3	9
ρ (Pitoa)	0.901	0.75	0	3	12
ρ (Djalingo)	1.958	1.371	0	3	12

Source: Authors calculations.

Note: risk aversion level that are found to be superior to 2 are arbitrarily set to 3 and those found inferior or equal to zero are set to zero.

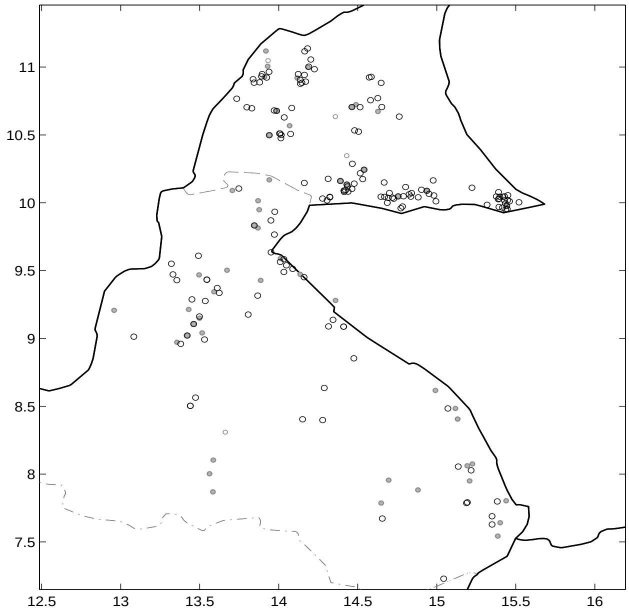

Figure 6: Sodecoton's surveys localisation: light grey dots for 2003, grey circles for 2006 and black circles for 2010.

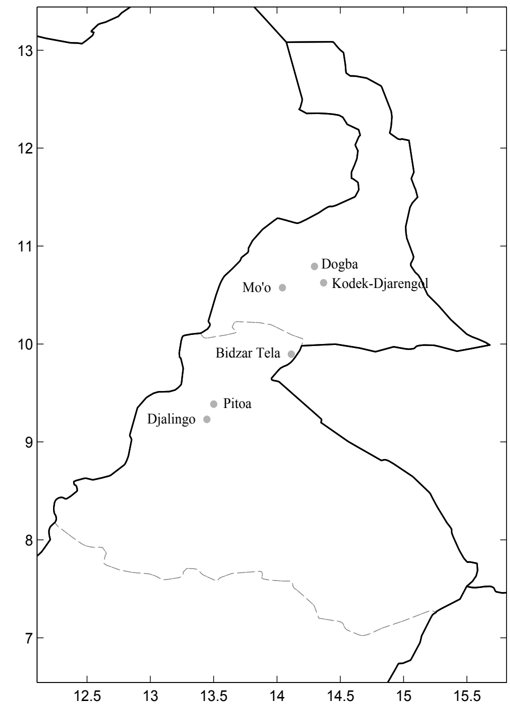

Figure 7: Villages in which lotteries were implemented.

E Income distribution and input and cotton prices inter and intra-seasonal variations

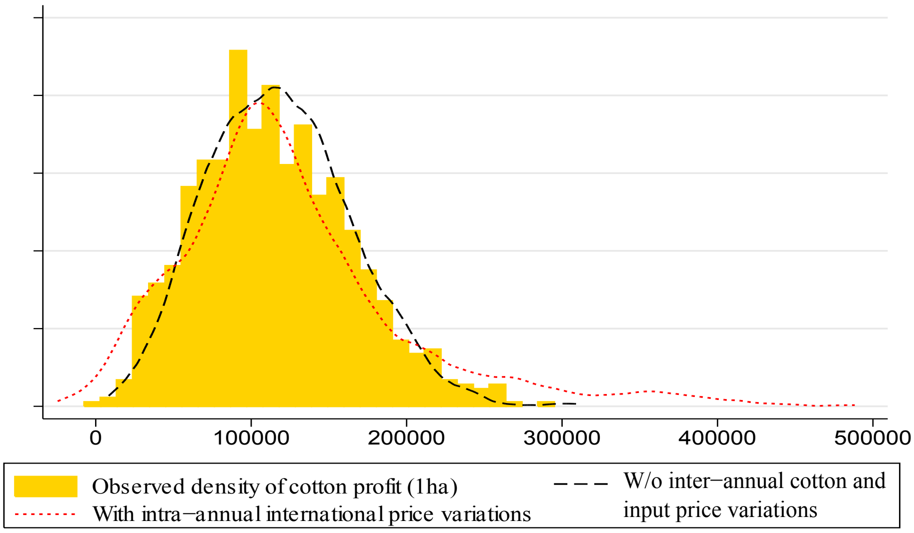

Figure 8: Distribution of cotton profit for one hectare, after reimbursement of inputs (in yellow the observed distribution, in black the kernel density of the simulated profit when considering fixed inter-annual cotton and input prices (to the period average) and in red the simulated distribution when adding international intra-seasonal prices variations).

Figure 8 shows the observed distribution of profit of one hectare of cotton, the distribution without any inter-seasonal cotton and input price variations (black) and the distribution with intra-seasonal price variations (red). The figure shows that using the average cotton purchasing price on the whole 1991-2004 period does not modify the profit distribution shape. Assuming an absence of inter-annual price variations thus does not radically modify the profit distribution. On the contrary, including intra-seasonal price variations (red line) has a much larger impact on income risk than inter-annual observed price variations, as argued in the section 4.3.