Weather index drought insurance: an ex ante evaluation for millet growers in Niger

Abstract

In the Sudano-Sahelian region, which includes South Niger, the inter-annual variability of the rainy season is high and irrigation is scarce. As a consequence, bad rainy seasons have a massive impact on crop yield and regularly entail food crises. Traditional insurance policies based on crop damage assessment are not available because of asymmetric information and high transaction costs compared to the value of production. We assess the risk mitigation capacity of an alternative form of insurance which has been implemented at a large scale in India since 2003: insurance based on a weather index. We compare the capacity of various weather indices to increase the expected utility of a representative risk-averse farmer. We show the importance of using plot-level yield data rather than village averages, which bias results due to the presence of idiosyncratic shocks. We also illustrate the need for out-of-sample estimations in order to avoid overfitting. Even with the appropriate index and assuming substantial risk aversion, we find a limited gain of implementing insurance, roughly corresponding to, or slightly exceeding, the cost observed in India of implementing such insurance policies. However, when we treat the plots with and without fertilisers separately, we show that the benefit of insurance is slightly higher in the former case. This suggests that insurance policies may increase, although to only a limited extent, the use of risk-increasing inputs like fertilisers and improved cultivars, hence average yields, which are very low in the region.

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

1 Introduction

Since the 1970s, the Sahel, including Niger, has suffered from severe food crises, partly because of droughts which occurred, particularly in 1973, 1984, 2004 and 2009. Moreover, because of the very high spatial variability of rainfall in the Sahel (Ali et al., 2005), many villages suffer from drought even in years which are not labeled as dry at the regional or national level. This situation contributes to recurrent malnutrition, especially in Niger (FEWSNET, 2010).

Food insecurity risks will probably increase over the coming decades because of population growth and climate change. On the latter point, although the impact of global warming on rainfall in this region is uncertain, the rise in temperature will most likely harm cereal yields (Roudier et al., 2011). Not only do droughts reduce yields when they occur, but they reduce the adoption of potentially yield-increasing agricultural practices (e.g. fertilisers, improved cultivars, etc.). Indeed, even if some of these practices may improve yields and farm income when averaged over several years, they may be detrimental in case of drought through increased input costs without significantly increased yields.

In this context, tools hedging farmers against droughts would be welcome. Unfortunately, traditional agricultural insurance policies cannot efficiently shelter farmers because they suffer from an information asymmetry between the farmer and the insurer, creating moral hazard situations and thus a need for costly damage assessment. An emerging alternative is insurance based on a weather index, which is used as a proxy for crop yield. In such a scheme, the farmer, in a given geographic area, pays an insurance premium every year, and receives an indemnity if the weather index of this area falls below a determined level (the strike). Index-based insurance does not suffer from the above-mentioned shortcoming: the weather index provides an objective and relatively inexpensive proxy for crop damages. However, its weakness is the basis risk, i.e. the imperfect correlation between the weather index and the yields of farmers contracting the insurance. The basis risk can be considered as the sum of two risks: first, the risk resulting from the index not being a perfect predictor of yield in general (the model basis risk). Second, the spatial basis risk: the index may not capture the weather effectively experienced by the farmer, all the more so if the farmer is far from the weather station(s) that provide data on which the index is calculated.

A rapidly growing body of literature has investigated the impact of crop insurance based on weather indices in developing countries: Berg et al. (2009) in Burkina Faso, De Bock (2010) in Mali, Chantarat et al. (2008) in Kenya, Molini et al. (2010) in Ghana and Zant (2008) in India. See Leblois and Quirion (2012) for a survey. Ex-post studies (Fuchs and Wolff, 2011; Stein, 2011; Hill and Viceisza, 2010; Cole et al. 2009; Giné and Yang, 2009 and Giné, Townsend, and Vickery, 2008) are still limited due to the recent development of such products. However, many recent reports describe existing programs (e.g. Hellmut et al., 2009 and Hazell et al., 2010).

This article aims at quantifying the benefit of a rainfall index-based insurance. We take advantage of a recent database of plot-level yield observations matched with a high density rain gauge network. We show that using village average yield distribution induces an upward bias in the estimation of benefits. Ex-ante simulations of insurance contracts indeed show that the insurance gain is limited by intra-village yield variations. We also demonstrate, in this particular case, the necessity to run out-of-sample estimations of the insurance impact in order to control for overfitting when calibrating its parameters. Such estimations validate the use of the most simple index, i.e. the cumulative rainfall over the growing season. Lastly, the database allows us to test whether and how much index-insurance may incite farmers to use more fertilisers by distinguishing between traditional technical itineraries and plots where intensification was encouraged. The best insurance contract however proved to have limited impact in terms of incentive towards intensification.

The rest of the article is organised as follows: we first describe the data and methods (section 2), then the results (section 3), and conclude with a fourth section. An annex provides additional results and robustness checks.

2 Data and method

2.1 Study area

Niger is the third producer of millet in the world, after India and Nigeria. Millet covers more than 70% of its cultivation surface dedicated to cereal (FAO, 2010) and is produced almost exclusively for internal consumption. In the context of rainfed agriculture and due to the dryness of the region, water availability is the major limiting factor of millet yields. The prevalence of millet, especially the traditional Haini Kiere, a photoperiodic and short cycle cultivar studied in this article, is due to its resistance to drought.

We study the Niamey squared degree area (Figure 1), because it is equipped with an exceptionally dense network of rainfall stations. Such infrastructure is needed in a region where spatial variability of rainfall is significantly high. We also dispose of seven years of yield observations (2004-2010) in ten villages. Yield observations have been collected by Agrhymet for a minimum of 30 farmers, randomly picked from each of the ten villages in 2004 and then annually surveyed in their plots until 2010. Yields were estimated using standard agronomic practices, i.e. using three distinct samples of plot production, weighting grains, counting the grains per ear of millet and the number of ears per surface unit. Every plot is situated at less than 2 kilometres from the nearest rainfall station, which is likely to limit the spatial basis risk mentioned above. Some additional information about the database can be found in previously published articles using the same data (Marteau et al., 2011).

In 2004, all plots were cultivated under traditional technical itineraries. In particular, very few mineral fertilisers, chemical herbicides or pesticides were used. From 2005 onwards, farmers continued to follow this traditional technical itinerary on a first plot, labeled the 'regular' plot, but freely received mineral fertilisers[1] for application on a second plot together with agronomic and technical advice from interviewers. The second plot is always situated in the immediate vicinity (within 50 meters) of the first.

It has to be mentioned that given the fact farmers have been studied for 7 years, a so-called "Hawthorne effect" could arise: farmers might have changed their behaviour by virtue of the fact that they are being studied for several years. For instance, they might adopt the technical itineraries recommended by agronomists, more than other farmers. Unfortunately, little can be done to detect or mitigate this effect.

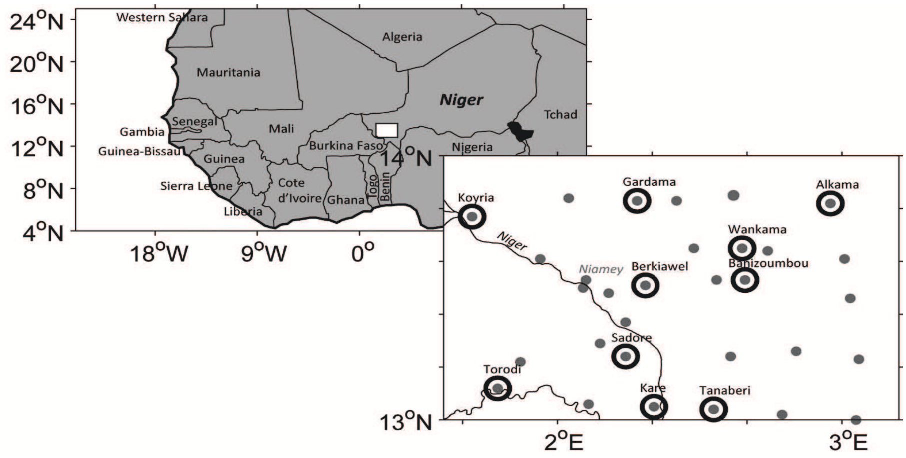

Figure 1: Rain gauges network and investigated villages (circled in black) across Niamey squared degree.

Table 1 displays the summary statistics of the regular plot. There is a high annual variability of yields across villages, with a coefficient of variation[2] (CV) of .33. Intra-village annual yield variation is however even higher (average CV=.55 over the ten villages), inducing a likely basis risk. It is due to a significant occurrence of idiosyncratic shocks, partly explained by insect ravages[3] that take place in more than 40% of the whole surveyed farmers' sample.

We value production at the millet post-harvest consumer price in Niamey over the 7 years, using monthly data from the SIM network[4] in order to compute income for each plot (*Plot income*). Fertiliser prices are taken from the 'Centrale d'Approvisionnement

[1] 50 kg per hectare (25 at hoeing and 25 when the plant runs to seed) i.e. more than the minimal level required (20 kg/ha) but less than the maximum (60 kg/ha) according to Abdoulaye and Sanders (2006).

[2] The CV is the standard deviation (std. dev.) divided by the mean.

[3] We check that their occurrence is not significantly correlated with rainfall in the Annex 5.3.2 (Table 13).

[4] Millet prices are the average prices of Katako market in Niamey, for the October-January period each year (94% of the sample has already been harvested at the end of October); the SIM network is an integrated information network across 6 countries in West Africa (resimao.org).

Table 1: Summary statistics: regular plots (2004-2010)

Variable	Mean	Median	Std. Dev.	CV	Min.	Max.	N
Plot yields (kg/ha)	596	500	383	.64	0	3 100	1 780
Plot income (FCFA/ha)	108 176	91 392	68 075	.63	0	566 634	1 780
Other crops income (FCFA)*	3 873	0	8 557	2.21	0	81 886	1 780
Other farm and non-farm incomes (FCFA)*	4 705	2 632	6 821	1.45	0	5 8333	1 780
Livestock and capital stock (FCFA)*	75 317	27 111	154 580	2.05	0	1 359 674	1 780

* Per household member, only available for 2006.

de la République du Niger'.

We use a 2006 socio-economic survey to estimate the capital stock, as well as farm and non-farm incomes. *Other crops income* is the value of declared production from other plots cultivated in 2006. *Other farm and non-farm incomes* are the 2006 whole farm income plus other incomes from declared activities: e.g. derived from livestock (fattening), fisheries, hunting, craft or salary earned by the grower. Monthly livestock prices over the period considered are taken from SIM Bétail, Niger: *Système d'Information sur les Marchés à Bétail.* Farm capital is quite limited and mainly constituted of plough and carts. The two last variables of Table 1 (*Other farm and non-farm incomes* and *Livestock and capital stock*) are computed per number of household members in order to estimate the actual share of income and stock available to the grower.

2.2 Indemnity schedule

Insurance indemnities are triggered by low values of an underlying index that is considered to explain yield variation. The indemnity is a step-wise linear function of the index with 3 parameters: the strike (S), i.e. the threshold triggering indemnity; 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. We thus have the following indemnification function depending on x, the meteorological index realisation:

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

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 except two dual strike point contracts: the BASIX contract launched in Andhra-Pradesh (Giné et al., 2008) and the contract simulated in De Bock et al., 2010.

2.3 Index choice

We first reviewed different indices that could be used in a weather index insurance, from the simplest to more complex ones. We tested the number of big rains (defined as superior to 15 and 20 mm.) often quoted by farmers (Roncoli et al., 2002) as a good proxy of yields, the number of dry spell episodes in the season, the Effective Drought Index (EDI, Byun and Wilhite, 1999) computed on a decadal basis, the Available Water Resource Index (AWRI, Byun and Lee 2002) and the Antecedent Precipitation Index (API, Shinoda et al., 2000, Yamagushi and Shinoda, 2002). Those indices are not presented in this paper because they provide a lower gain than those we retained or no gain at all, expressed in certain equivalent income.

The indices retained in the paper are listed below by increasing complexity. The first is the cumulative rainfall (CR) over the crop growth period, cutting off low daily precipitations ($< .85$ mm following Odekunle, 2004) that probably evaporated entirely. Computing this index, as well as the next ones, necessitates determining the beginning of the crop growth period. Using the actual sowing date to determine the beginning of the crop growth period in an insurance contract is difficult because it cannot be observed costlessly by the insurer. Thus we compare two growth phase schedules: the one observed referred to as *obs* and the one simulated following Sivakumar (1988), referred to as *siva* in the paper. The onset of the simulated growing season is triggered by a cumulative rainfall of over 20 mm in two days followed by one month without seven consecutive days of dry spells (with no significant rainfall, i.e. superior to .85 mm) after 1 May. The offset is the day that follows 20 consecutive days without rainfall after 1 September.

We then consider a refinement (referred to as BCR) of each of these simple indices 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).

A further refinement is to distinguish various phases during the crop growth period in the calculation of the index. Hence we use a weighted average of cumulative rainfall during these phases, following Alhassane (1999) and Dancette (1983). Weights of each period represent water needs as a share of available water, approximated by cumulative rainfall during the period, in order to represent the contribution of rainfall of each phase to crop growth. This index is thus very similar to the Water Requirement Satisfaction Index (WRSI), the most commonly used index in the literature. The indices are referred to as $WACR$ when daily rainfall is not bounded and $WABCR$ when it is. Table 2 displays the descriptive statistics of the above-mentioned indices over the study period. The trade-off between accuracy and the simplicity of the index, brought up by emerging literature (Patt et al., 2009), suggests to use the most transparent index among indices reaching similar outcomes.

2.4 Parameter optimization

The literature offers multiple different objective functions, such as the semi variance (or downside risk as used in Vedenov and Barnett, 2004) or the mean-variance criterion. The former only takes risk (variance minimization) into account, without considering the

Table 2: Summary statistics: growing season rainfall indices (2004-2010)

Variable	Mean	Std. Dev.	Min.	Max.	N
CR_{obs} (mm)	452.754	120.359	61.469	685.199	1 780
BCR_{obs} (mm)	397.417	99.95	61.469	565.468	1 780
CR_{siva} (mm)	475.072	95.432	263.816	735.89	1 780
BCR_{siva} (mm)	417.058	73.524	262.199	574.062	1 780
$WACR_{siva}$ (mm)	241.332	62.214	33.543	365.543	1 780
$WABCR_{siva}$ (mm)	275.767	75.026	33.543	453.566	1 780

trade-off with a reduction of average consumption level (as emphasized by Osgood and Shirley, 2010). The mean-variance criterion accounts for both the consumption level and the risk, but it weights risk with an ad-hoc parameter. We finally retained the power or Constant Relative Risk Aversion (CRRA) utility function in order to compute the variation of certain equivalent income (CEI). Power utility functions have the advantage of facilitating the comparison of results for different risk aversions and of using a parameter that has been estimated in many contexts, in particular in many developing countries. CRRA appears appropriate to describe farmers' behaviours according to Chavas and Holt (1996) or Pope and Just (1991). Moreover, Andreoni and Harbaugh (2009) who tested the robustness of 5 of the most often used hypotheses in the field of utility, found that "the expected utility model does unexpectedly well" and that "if a researcher would like to impose the simplification of CRRA utility, this likely comes at a small cost on average". We thus consider the following utility function:

$$U(Y_i) = \frac{(W_0 + Y_i)^{(1-\rho)}}{(1-\rho)} \tag{2}$$

Where Y_i is a individual-year income observation, the individual being the plot or the village depending on the simulation under consideration, W_0 is the non-millet related income and ρ is the relative risk aversion parameter. In sections 3.1 and 3.2, we use yields, in kg per hectare, as a proxy for income. This neglects the use of purchased inputs such as mineral fertilisers but their use is very limited[5]. It also neglects the inter-annual variations of prices, the impact of which on insurance gain is negligible, as shown in Table 12. Section 3.3 is devoted to the introduction of millet and input prices in the analysis. Hence in this section, Y_i is the income in monetary units. The certain equivalent income corresponds to:

$$CEI(\tilde{Y}) = \Big((1-\rho) \times EU(\tilde{Y})\Big)^{\frac{1}{1-\rho}} - W_0, \qquad \tilde{Y} = \{Y_1, ..., Y_N\} \tag{3}$$

With $EU(\tilde{Y})$ the expected utility of the vector of income realizations ($\tilde{Y}$). The non-millet related income (W_0) is considered as certain, following Gray et al. (2004). It lowers insurance gains in terms of certain equivalent income by increasing the certain part of total income (cf. Table 13 in the Annex). It also allows the premium to be superior

[5] Plots with encouragement to fertilise will be considered in section 3.3.

to the lowest yield observation. The 2006 socio-economic survey shows that the average for capital detention, *Other farm and non-farm incomes*, is more than half the average income for one hectare of production (as displayed in Table 1). This is consistent with Abdoulaye and Sanders (2006) who found millet representing about 40 to 60% of total revenues. Nevertheless, there is pronounced heterogeneity among such incomes (CV of about 2[6]), half the farmers having less than 27 000 FCFA of livestock (and 75% of them having less than the average level), which leaves them without any buffer stock for facing weather and production shocks. Looking at the median of these variables to get the situation of an average millet grower, other incomes represent about 32.5% of the income for one hectare of millet. We thus set W_0 at a third of the average yield (about 200 kg of millet) multiplied by the average millet price over the period considered. However, when running robustness checks to the calibration of this parameter, the scope of the results does not change dramatically and the order of indices remains the same (as displayed in Table 13 of the Annex in section 5.3.2). We tested a range of values for the relative risk aversion parameter from .5 to 4. This range encompasses the values usually used in development economics literature (Coble et al., 2004; Wang et al., 2004; Carter et al., 2007 and Fafchamps, 2003; see Cardenas and Carpenter, 2008 for a review of econometric studies that estimate this parameter). A relative risk aversion of 4 may seem high but empirical estimates of relative risk aversion indicate a wide variation across individuals. If, therefore, insurance is not compulsory, only the most risk-averse farmers are likely to be insured (Gollier, 2004).

The insurance contract parameters S, M and λ are optimized in order to maximize the certain equivalent income of risk averse farmers given by equation (3) with the following income after insurance:

$$Y^I = Y(x) - P(S^*, M^*, \lambda^*, x) + I(S^*, M^*, \lambda^*, x) \tag{4}$$

Y^I is the income after indemnification, Y the income before insurance, P the premium, I the indemnity and x the rainfall index realisations associated with each plot. We used a grid optimization process to maximize the objective function and bounded the premium to the minimum endowments. The loading factor is a percentage of total indemnifications over the whole period (β, fixed at 10% following a private experiment that took place in India, cf. section 3.4), plus a transaction cost (C) for each indemnification, fixed to one day of rural labor wage.

$$P = \frac{1}{N}\big[(1+\beta) \times \sum_{i=1}^{N} I_i\big(S^*, M^*, \lambda^*, x_i\big) + C \times \sum_{i=1}^{N} F_i\big], \text{ with } F_i = \begin{cases} 1 \text{ if } I_i > 0 \\ 0 \text{ if } I_i = 0 \end{cases} \tag{5}$$

[6] Due to the large number of livestock Fulani or Tuareg people (representing 12% of the sample) often own.

3 Results

For the first two parts of this section we will consider only regular plots (1780 observations), on which traditional technical itineraries are followed (for the period 2004-2010). The last part will compare different technical itineraries for the 2005-2010 sub-period for which data for both plots (regular and 'encouragement' plots, 2952 observations) are available.

3.1 Plot-level vs. aggregated data

We show that calibrating insurance parameters on village average yield can have undesired consequences due to high intra-village yield variations. Calibration on plot-level data allows taking intra-village yield variations and idiosyncratic shocks into consideration, which is rarely the case due to a lack of such plot-level data.

In tables 3, 4, and 5 we present the average farmer's gain from insurance in certain equivalent income for each index, respectively calibrated for the whole sample (using the entire vector with N=1780), then each village's average yields (N=60) and lastly testing this latter calibration on the whole sample. This is done to test whether the calibration of parameters significantly differs when considering intra-village yield variations. This CEI gain when insured (CEI^I) is expressed in percent of the CEI without insurance. The CEI gain in percent is:

$$\frac{CEI^I - CEI}{CEI} \tag{6}$$

The indemnity schedules of the CR_{siva} contract and the parameter calibrations for all indices are respectively displayed in Figure 3 and Tables 10 and 11 of the Annex. The premium level goes from 16.8 ($\rho = .5$) to 24.2 kg ($\rho = 4$) of millet that represents about 5% of average yield, which seems affordable but is significant when compared to insurance gain.

Table 3: Average income gain of index insurance *calibrated on the whole sample* (N=1780)

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CEI gain of CR_{obs}-based insurance	.00%	.24%	.94%	1.93%	3.08%
CEI gain of BCR_{obs}-based insurance	.00%	.28%	1.27%	2.40%	3.68%
CEI gain of CR_{siva}-based insurance	.00%	**.31**%	1.27%	2.62%	4.65%
CEI gain of BCR_{siva}-based insurance	.00%	.29%	**1.52**%	**3.13**%	**5.21**%
CEI gain of $WACR_{siva}$-based insurance	.00%	.16%	.95%	2.06%	3.52%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.23%	1.38%	2.92%	4.95%

The main results are the following. Firstly, none of the tested insurance contracts are found to increase CEI when assuming the lowest level of risk aversion (.5). The explanation is that with such a low risk aversion, the potential benefit of insurance is too low to compensate the loading factor plus the transaction cost. With higher levels of risk aversion, CEI does increase but by a very modest margin (+5.21% at most).

Table 4: Average income gain of index insurance *calibrated on village average yields values* (N=60)

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CEI gain of CR_{obs}-based insurance	.00%	**.27**%	1.20%	2.64%	4.48%
CEI gain of BCR_{obs}-based insurance	.00%	.23%	1.06%	1.96%	2.87%
CEI gain of CR_{siva}-based insurance	.00%	**.27**%	1.15%	2.57%	4.41%
CEI gain of BCR_{siva}-based insurance	.00%	.26%	**1.44**%	**2.95**%	**4.81**%
CEI gain of $WACR_{siva}$-based insurance	.00%	.11%	1.00%	2.27%	3.91%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.13%	.85%	1.76%	2.91%

Table 5: Average income gain of index insurance *calibrated on village average yields values and tested on the whole sample (N=1780)*

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CEI gain of CR_{obs}-based insurance	.00%	.24%	.91%	1.71%	2.48%
CEI gain of CR_{obs}-based insurance	.00%	.08%	1.26%	2.32%	3.36%
CEI gain of CR_{siva}-based insurance	.00%	**.31**%	1.25%	2.54%	4.30%
CEI gain of CR_{siva}-based insurance	.00%	.29%	**1.52**%	**3.04**%	**4.92**%
CEI gain of CR_{siva}-based insurance	.00%	.16%	.93%	1.80%	2.61%
CEI gain of CR_{siva}-based insurance	.00%	.12%	1.06%	2.38%	4.16%
Variations in CEI gain compared to calibration on plot-level sample					
CR_{obs}-based insurance	n.a.	-2.55%	-2.93%	-11.41%	-19.68%
BCR_{obs}-based insurance	n.a.	-71.26%	-.72%	-3.19%	-8.58%
CR_{siva}-based insurance	n.a.	-.06%	-1.14%	-2.76%	-7.50%
BCR_{siva}-based insurance	n.a.	-.39%	-.18%	-2.90%	-5.41%
$WACR_{siva}$-based insurance	n.a.	.02%	-1.34%	-12.56%	-26.08%
$WABCR_{siva}$-based insurance	n.a.	-46.02%	-22.87%	-18.23%	-15.99%

n.a.: not applicable.

Secondly, more complex indices do not always lead to a larger gain: bounding daily rainfall to a maximum of 30 mm (BCR) performs better than simple cumulative rainfall but taking the weighted averages does not increase relative CEI gains.

Thirdly, the insurance gain is higher when dealing with simulated crop growth cycles than with observed ones. Such a peculiar result could be explained by the use of water reserves constituted before the actual sowing date and that are available in the soil. As shown by Marteau et al. (2001) the observed sowing date occurs, in most cases, after the onset of the rainy season. This result also shows that costly observation of sowing date does not seem to be needed[7].

As shown by the comparison of Tables 3 and 5, taking the average value for each village leads to a miscalculation of insurance parameters with a concave utility function that also depends on intra-village income distribution. In our case the misapprehension of village yield distribution leads to an over-insurance situation, i.e. a higher indemnity M and thus

[7] The emergeance of new information technology can make the collection of such information easier. Cell phones could, for instance, be used for reporting sowing dates with high frequency and accuracy at low cost. Those technologies, even if very cheap, would rely on the availability of cell phones in each community, and were only available to 4% of the population of Niger in 2006 according to Aker (2008). Moreover, even when technologies are cheap, their price can still be significant in regards to the low area cultivated and the budget constraints of smallholders that are studied in this article

a premium 25% higher on an average: cf. Tables 10 and 11 in the Annex. The presence of yield heterogeneity within villages modifies the effective gain of an insurance calibrated on village averages. The average loss from average yield calibration is significant (12%) but its size depends on the index. It stresses the usefulness to calibrate insurance parameters on observed yields at the plot level.

3.2 Need for cross-validation

In the previous section, we optimized the parameters and evaluated the insurance contracts on the same data. This creates a risk of overfitting due to the fact that parameters will not be calibrated and applied to the same data in an actual insurance implementation. We can identify such a phenomenon by running a cross-validation analysis (as do Vedenov and Barnett, 2004 and Berg et al., 2009). We thus run a 'leave one (village) out' method, optimizing the 3 parameters of the insurance contract for each village using data from the 9 other villages. We apply this method for each of the three different indices and on the whole sample of farmers' regular plots. As shown by Figures 4 to 9 in the Annex, the strike level is relatively robust across out-of-sample estimations and comparable to the in-sample case. However the maximum indemnity M is less robust and we will show later that this causes severe reductions in CEI gain.

In the out-of-sample estimations the insurer can be better off or worse off than in the corresponding contract optimized with the in-sample method[8]. Table 6 shows the gain in CEI when the insurer can either endure losses or obtain benefits, due to the bad calibration that arises from the fact that insurance is assessed and calibrated on different datasets. It is thus important to keep in mind that in a real insurance project, either the insurer or the farmers would suffer from this (partly unavoidable) bad calibration. In our case study, calibrating insurance parameters on the nine other villages leads to heightening the variation of the insurer's benefit across different calibrations.

[8] This is also the case in Berg et al. (2009, Fig. 4)

Table 6: Average CEI gain of leave-one-(village)-out calibration index insurance, with insurer gain or losses.

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CEI gain of CR_{obs}-based insurance for farmers	-0.175%	-.02%	-.23%	-.28%	-.33%
Insurer gain (kg/ha) with CR_{obs}-based insurance	1.34	2.48	3.47	3.71	2.72
Insurer gain (perc. of total indem.) with CR_{obs}-based insurance	16.29%	17.69%	20.15%	23.79%	18.90%
CEI gain of BCR_{obs}-based insurance for farmers	-0.177%	-.41%	.28%	.80%	1.31%
Insurer gain (kg/ha) with BCR_{obs}-based insurance	0.44	4.10	3.95	3.20	3.01
Insurer gain (perc. of total indem.) with BCR_{obs}-based insurance	10.28%	21.95%	19.20%	16.76%	17.78%
CEI gain of CR_{siva}-based insurance for farmers	.57%	-.10%	1.06%	1.66%	2.77%
Insurer gain (kg/ha) with CR_{siva}-based insurance	-2.81	2.16	0.55	2.03	3.54
Insurer gain (perc. of total indem.) with BCR_{obs}-based insurance	-54.33%	14.63%	2.93%	9.99%	18.18%
CEI gain of BCR_{siva}-based insurance for farmers	-0.336%	.43%	.78%	1.43%	2.47%
Insurer gain (kg/ha) with BCR_{siva}-based insurance	1.27	0.13	2.44	2.26	2.01
Insurer gain (perc. of total indem.) with BCR_{obs}-based insurance	69.02%	.58%	9.93%	9.76%	9.31%
CEI gain of $WACR_{siva}$-based insurance for farmers	-0.080%	1.51%	2.63%	3.49%	5.85%
Insurer gain (kg/ha) with $WACR_{siva}$-based insurance	0.03	-4.13	-4.59	-3.85	-4.86
Insurer gain (perc. of total indem.) with BCR_{obs}-based insurance	1.84%	-18.14%	-18.21%	-16.35%	-21.70%
CEI gain of $WABCR_{siva}$-based insurance for farmers	-0.300%	.69%	.94%	1.71%	3.31%
Insurer gain (kg/ha) with $WABCR_{siva}$-based insurance	1.15	-1.22	1.31	1.17	-0.14
Insurer gain (perc. of total indem.) with BCR_{obs}-based insurance	69.92%	-5.73%	5.53%	5.28%	-.65%

Table 7 shows the insurance gain in out-of-sample when redistributing to farmers of insurer profits (losses) that are superior (inferior) to the 10% charging rate we fixed in the previous sections. This artificially keeps the insurer out-of-sample gain equal to the in-sample case and thus allows comparison with in-sample calibration estimates. The insurance benefit for farmers drops by an average of 71% .

The ranking of the indices also changes compared to the in-sample calibration: while simulated crop cycles still perform better than observed ones, the preceding result that bounding daily rainfall to 30 mm makes the index more accurate no longer holds for simulated crop cycles: under out-of-sample calibration, for $\rho \geq 3$, the simplest index, cumulated rainfall (CR_{siva}), brings the best outcome.

3.3 Potential intensification due to insurance

As pointed out by Zant (2008), our ex ante approach does not take into account the potential intensification due to insurance supply. Indeed, many agricultural inputs, especially fertilisers, increase the average yield but also the risk. If the rainy season is bad, the farmer still has to pay for the fertilisers even though the increase in yield will be very limited or even nil. The literature on micro-insurance suggests that the supply of risk-mitigating products could increase the incentive to use more yield-increasing and risk-increasing inputs (Hill, 2010). It could also foster input credit demand thanks to lower default rates, as tested by Giné and Yang (2009).

To address the first point we use additional data concerning 'encouragement' plots, where inputs (following a micro-dose fertilisation process) are systematically used because they are freely allocated by survey officers. Each farmer has a 'regular' plot and

Table 7: Average income gain of leave one (village) out calibration index insurance, with equal redistribution across farmers of residual gains or losses from the charging rate (10% of total indemnification) by the insurer.

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CEI gain of CR_{obs}-based insurance	-.07%	.20%	.22%	.40%	.17%
CEI gain of BCR_{obs}-based insurance	-.17%	.06%	.76%	1.20%	1.81%
CEI gain of CR_{siva}-based insurance	**-.05%**	.04%	.72%	**1.66%**	**3.36%**
CEI gain of BCR_{siva}-based insurance	-.13%	-.01%	**.78%**	1.41%	2.42%
CEI gain of $WACR_{siva}$-based insurance	-.11%	**.17%**	.81%	1.56%	3.21%
CEI gain of $WABCR_{siva}$-based insurance	-.11%	.00%	.67%	1.38%	2.46%
Loss in CEI gain (compared to the in-sample calibration)					
CR_{obs}-based insurance	n.a.	-16.95%	-76.19%	-79.28%	-94.48%
BCR_{obs} -based insurance	n.a.	-79.92%	-39.97%	-49.88%	-50.89%
CR_{siva}-based insurance	n.a.	-86.38%	-43.21%	-36.51%	-27.73%
BCR_{siva}-based insurance	n.a.	-103.97%	-49.01%	-54.95%	-53.55%
$WACR_{siva}$-based insurance	n.a.	7.73%	-14.23%	-24.11%	-8.93%
$WABCR_{siva}$-based insurance	n.a.	-102.12%	-51.52%	-52.54%	-50.38%

n.a.: not applicable.

an 'encouragement' plot, the latter being available for only the 2005-2010 period. Our hypothesis is the following: since the cost of a bad rainy season is, in most cases, higher for intensified production, the insurance gain should also be higher. In such a case insurance should foster intensification and therefore bring a higher gain.

Table 8 displays the summary statistics of the indices over the sub-period considered in this section. Observed yields are 15.1% higher in the plots where fertilisation was encouraged. On-farm income of plots where mineral or both organic and mineral fertilisers were used is about 4.4% superior in average[9] but with higher risk compared to regular plots that were grown under traditional technical itineraries. The CV of on-farm income is 6% higher in the encouragements plots than in the regular plots. This may explain why fertilisers are seldom used in this area when they must be purchased.

Table 9 displays the in-sample gain from insurance, when dealing with plot income instead of raw yields, using the same objective function and the same optimization process. As shown in Table 12 in the Annex, results are not altered by taking the income level for one hectare. The main differences between Table 3 and Table 9 (considering only the part dedicated to regular plots in Table 9) are thus driven from the change in the sample (dropping the year 2004 in Table 9).

Looking at the CEI gain to use fertilisers, we see that insurance is not a powerful incentive to use costly inputs. This is illustrated in Figure 2 which displays the CEI according to the risk aversion parameter, arrows showing the level under which growers will use fertilisers (augmenting risk and average income) without and with index-based insurance. The risk aversion threshold under which farmers have an interest in using fertilisers is a bit higher with insurance (dotted arrow) but only slightly. The area in light

[9] In this calculation, we assume that farmers have to buy the fertilisers (in the 'encouragement plots', they receive them for free).

Table 8: Summary statistics: all plots (2005-2010)

Variable	Mean	Std. Dev.	CV	Min.	Max.	N
Farm yields (kg/ha)	579.19	368.53	.64	0	3300	2 952
Plot income (FCFA/ha)	101 637.70	68 154.46	.67	-5 001.62	593 692	2 952
Other crops income (FCFA)*	42 317.23	98 015.53	2.32	0	1 080 833.13	2 952
Other farm and non-farm incomes (FCFA)*	4 743.83	6 872.70	1.45	0	5 8333.33	2 952
Livestock and capital stock (FCFA)*	78 643.36	159 825.72	2.03	0	1 359 674.13	2 952
CR_{obs} (mm)	471.28	99.29	.21	293.37	735.89	2 952
BCR_{obs} (mm)	412.68	74.98	.18	266.68	574.06	2 952
CR_{siva} (mm)	451.28	125.74	.28	61.47	685.20	2 952
BCR_{siva} (mm)	393.94	102.53	.26	61.47	565.47	2 952
$WACR_{siva}$ (mm)	277.79	80.00	.29	33.54	453.57	2 952
$WABCR_{siva}$ (mm)	241.31	65.63	.27	33.54	365.54	2 952
Among which						
Regular plots:						
Farm Yields (kg/ha)	538.55	347.61	.65	0	3 100	1 476
On-farm income (FCFA)	99 439.26	65 003.70	.65	0	566 634.94	1 476
Encouragement plots:						
Farm Yields (kg/ha)	619.83	384.16	.62	31	3 300	1 476
On-farm income (FCFA)	103 836.15	71 120.02	.69	-5 001.62	593 692	1 476

* Per household member, in 2006.

Table 9: In-sample average gain of insurance depending on the index and risk aversion parameter.

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
All sample (N=2952)					
CEI gain of CR_{obs}-based insurance	.00%	.08%	.61%	1.25%	1.92%
CEI gain of BCR_{obs}-based insurance	.00%	.13%	1.13%	2.47%	4.12%
CEI gain of CR_{siva}-based insurance	.00%	.13%	1.08%	2.56%	4.49%
CEI gain of BCR_{siva}-based insurance	.00%	**.14**%	**1.14**%	**2.71**%	**4.78**%
CEI gain of $WACR_{siva}$-based insurance	.00%	.03%	.58%	1.43%	2.52%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.03%	.44%	1.12%	1.96%
Regular plots (N=1476)					
CEI gain of CR_{obs}-based insurance	.00%	.10%	.51%	1.00%	1.48%
CEI gain of BCR_{obs}-based insurance	.00%	.12%	.96%	1.94%	3.05%
CEI gain of CR_{siva}-based insurance	.00%	.21%	1.00%	2.35%	4.15%
CEI gain of BCR_{siva}-based insurance	.00%	.22%	.99%	2.32%	4.06%
CEI gain of $WACR_{siva}$-based insurance	.00%	.01%	.67%	1.62%	2.90%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.01%	.55%	1.38%	2.38%
Encouragement plots (N=1476)					
CEI gain of CR_{obs}-based insurance	.00%	.05%	.70%	1.49%	2.33%
CEI gain of BCR_{obs}-based insurance	.00%	.15%	1.30%	3.01%	5.16%
CEI gain of CR_{siva}-based insurance	.00%	.05%	1.16%	2.76%	4.82%
CEI gain of BCR_{siva}-based insurance	.00%	.05%	1.29%	3.09%	5.42%
CEI gain of $WACR_{siva}$-based insurance	.00%	.04%	.48%	1.25%	2.16%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.04%	.33%	.87%	1.57%

(dark) grey on the left (right) corresponds to the risk aversion levels for which farmers' certain equivalent of their expected income is higher without (with) fertilisation. The medium grey area in-between corresponds to the values of risk aversion for which farmers will use fertilisation only if a *BCR*-based insurance is supplied. Moreover, the size of the latter area that corresponds to the insurance intensification incentive shrinks with the level of certain wealth (W_0). We display identical figures, for the 5 other indices considered in the paper, in the annex.

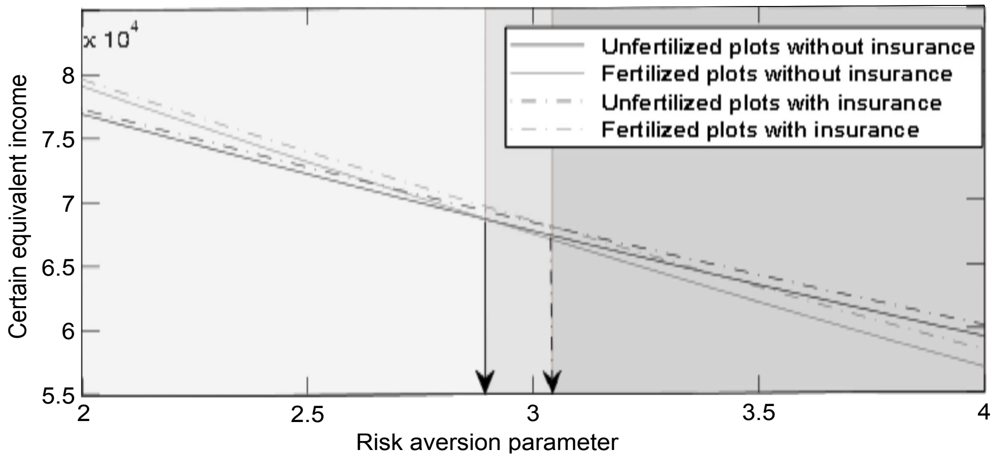

Figure 2: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with CR_{obs}-based insurance (dotted lines), according to the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income. The light grey area corresponds to the level of risk aversion for which no fertilisers are used, the dark grey one for which they are used with or without insurance and the medium grey area to the levels for which fertilisers are used only if CR_{obs}-based insurance is supplied.

3.4 Comparison of cost and benefit of insurance

Up to this point we have used ad-hoc insurance costs. We now try to assess its level using a private experiment of weather index-based insurance, without subsidies, that has been taking place since 2003 in 8 districts in India (Chetaille, et al., 2010). The annual number of insurance contracts sold reached 10,000 in 2010. The average loss ratio (total claims divided by the sum of collected premiums) for the 6 years was 65%. The total cost was about US$ 7 000 per year (US$1.3 per policy sold), among which 30% is dedicated to design and implementation (ICICI Lombard), another 30% to reinsurance (SwissRe) and 40% to distribution (Basix). Each institution declared to make profits amounting to about 10% of its total sales.

In our case a 1% increase in CEI represents 4.9kg of millet for $\rho = 2$, which can be valued at about US$ 1.8 per hectare when millet is valued at the period average price (188 FCFA/kg) for the period considered. Given the distribution of income among regular plots, the insurance gain should exceed 0.7% of CEI in order to be profitable to the whole system composed of farmers and the insurer. 0.7% of CEI corresponds to US$1.3, the estimated cost of a weather index-based insurance policy in India. We found in section 3.2 that the gain from insurance is lower in out-of-sample than in in-sample estimations. For most indices, the insurance is thus worth implementing if farmers' risk aversion parameters are equal or superior to 2.

Moreover, in section 3.3 we show that the insurance impact on CEI could be higher when production is intensified but only a slightly larger part of farmers would use costly inputs. Finally, it seems that the performance of insurance could hardly become significantly larger than its cost in our case, even when considering the potential incentive to intensification.

4 Conclusions

The article highlights four major conclusions for designing and assessing weather-index insurance policies for agriculture. Firstly, it underlines the need to use plot-level data to calibrate and get a robust estimation of the ex ante impact of insurance. This is particularly important in our case study (millet in South West Niger), where intra-village yield variations are high and the causes of low yields are numerous. Secondly, the outcomes of simple indices are comparable to those of more complex ones. More specifically, within an in-sample assessment, the best index is a simple cumulative rainfall over the growing period, with a cut-off for daily rains exceeding a certain threshold. Within an out-of-sample (leave-one-out) assessment, the best index is even simpler, i.e. the cumulative rainfall over the growing period. This second conclusion is welcome since a simple index is easier to understand for farmers. Our third conclusion is also welcome: indices based on a simulated sowing date perform at least as well as those based on observed sowing dates which would be costly to collect.

However, our final conclusions are more dismal: our out-of-sample estimations show that mis-calibration is a risk for both the insurer and farmers, and that for the benefit from index-based insurance to be higher than a very rough estimation of its implementation cost (based on evidence from India), a rather high risk aversion (typically superior to 2) is required.

Moreover, taking the potential fertilisation into account does not seem to change this conclusion, since insurance supply could hardly foster additional costly input use under our set of hypotheses. The last two results emphasize the need for more research in order to evaluate the potential of such products in the case of low intensification, shown by most food crop production systems in sub-Saharan Africa.

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5 Annex

5.1 In-sample calibrations

Figure 3 shows the indemnification of the CR_{siva}-based insurance across the area and over the period considered. In spite of a relatively low basis risk: most of the low yield situations are indeed insured, the certain equivalent income gain is rather low (1.27%).

Table 10: Parameters of index insurance policy: *calibrated on the whole sample*

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
M (maximum indemnification) in kg of millet					
CR_{obs}-based insurance	0	129	109	109	99
BCR_{obs}-based insurance	0	129	129	119	109
CR_{siva}-based insurance	0	139	149	119	119
BCR_{siva}-based insurance	0	119	139	129	119
$WACR_{siva}$-based insurance	0	119	129	129	119
$WABCR_{siva}$-based insurance	0	109	129	119	109
λ (slope related parameter)					
CR_{obs}-based insurance	0	1	1	1	1
BCR_{obs}-based insurance	0	.95	.95	.95	.95
CR_{siva}-based insurance	0	1	1	1	1
BCR_{siva}-based insurance	0	1	1	1	1
$WACR_{siva}$-based insurance	0	1	1	1	1
$WABCR_{siva}$-based insurance	0	1	1	1	1
Strike					
CR_{obs}-based insurance	.	370	389	389	389
BCR_{obs}-based insurance	.	350	350	350	350
CR_{siva}-based insurance	.	303	303	359	359
BCR_{siva}-based insurance	.	321	321	321	321
$WACR_{siva}$-based insurance	.	197	197	197	197
$WABCR_{siva}$-based insurance	.	187	187	187	187
Annual premium in kg of millet					
CR_{obs}-based insurance	.00	16.45	23.65	23.65	21.60
BCR_{obs}-based insurance	.00	24.25	24.25	22.46	20.67
CR_{siva}-based insurance	.00	16.77	17.92	24.23	24.23
BCR_{siva}-based insurance	.00	26.08	30.24	28.16	26.08
$WACR_{siva}$-based insurance	.00	15.22	17.86	16.54	15.22
$WABCR_{siva}$-based insurance	.00	26.08	28.16	28.16	26.08
Rate of indemnification					
CR_{obs}-based insurance	0%	10.56%	10.56%	10.56%	17.70%
BCR_{obs}-based insurance	0%	19.04%	19.04%	19.04%	19.04%
CR_{siva}-based insurance	0%	11.12%	11.12%	18.76%	18.76%
BCR_{siva}-based insurance	0%	16.40%	16.40%	16.40%	16.40%
$WACR_{siva}$-based insurance	0%	19.04%	19.04%	19.04%	19.04%
$WABCR_{siva}$-based insurance	0%	12.08%	12.08%	12.08%	12.08%

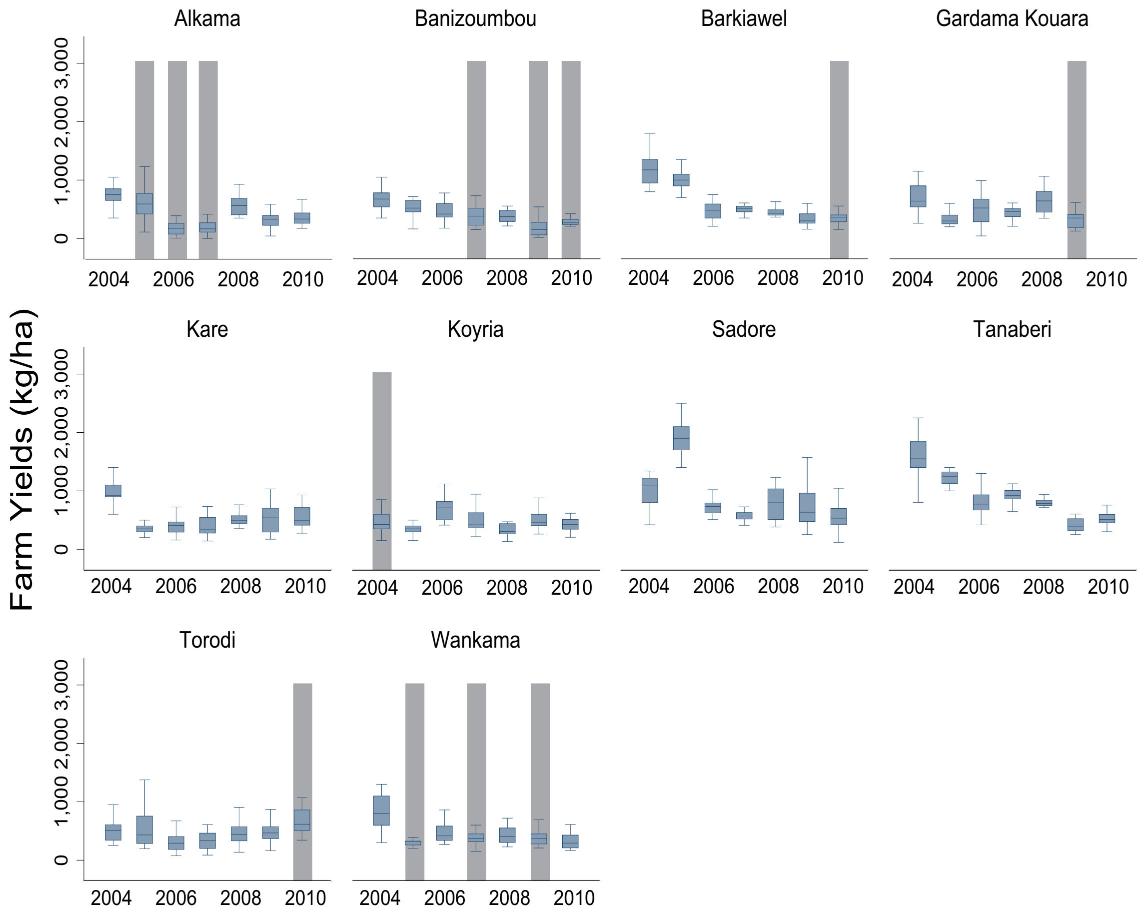

Figure 3: Indemnities (grey bars: amount to 129kg/ha) of a CR_{siva} based insurance for ρ=2 and box plot of yields by village over the 2004 to 2010 period.

Table 11: Insurance contract parameters *calibrated on village average yields values*

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
M (maximum indemnification) in kg					
CR_{obs}-based insurance	.	142	142	153	153
BCR_{obs}-based insurance	.	131	142	142	131
CR_{siva}-based insurance	.	142	142	153	153
BCR_{siva}-based insurance	.	131	153	164	164
$WACR_{siva}$-based insurance	.	110	131	142	142
$WABCR_{siva}$-based insurance	.	110	121	142	142
λ (slope related parameter)					
CR_{obs}-based insurance	.	1	1	1	1
BCR_{obs}-based insurance	.	.95	.95	.95	.95
CR_{siva}-based insurance	.	1	1	1	1
BCR_{siva}-based insurance	.	1	1	1	1
$WACR_{siva}$-based insurance	.	1	1	1	1
$WABCR_{siva}$-based insurance	.	1	1	1	1
Strike					
CR_{obs}-based insurance	.	370	389	389	389
BCR_{obs}-based insurance	.	334	350	350	350
CR_{siva}-based insurance	.	303	360	360	360
BCR_{siva}-based insurance	.	321	321	321	321
$WACR_{siva}$-based insurance	.	174	198	198	198
$WABCR_{siva}$-based insurance	.	188	216	188	188
Annual premium in kg of millet					
CR_{obs}-based insurance	.00	16.48	32.96	35.40	35.40
BCR_{obs}-based insurance	.00	17.44	25.90	25.90	23.97
CR_{siva}-based insurance	.00	16.48	28.25	30.34	30.34
BCR_{siva}-based insurance	.00	28.33	32.87	35.14	35.14
$WACR_{siva}$-based insurance	.00	14.64	28.07	18.83	18.83
$WABCR_{siva}$-based insurance	.00	18.30	30.51	32.96	32.96
Rate of indemnification					
CR_{obs}-based insurance	0%	10.56%	17.70%	17.39%	17.39%
BCR_{obs}-based insurance	0%	19.04%	19.04%	18.84%	18.84%
CR_{siva}-based insurance	.11%	11.07%	18.76%	20.29%	20.29%
BCR_{siva}-based insurance	.22%	10.67%	16.40%	15.94%	15.94%
$WACR_{siva}$-based insurance	0%	14.83%	20.73%	20.29%	20.29%
$WABCR_{siva}$-based insurance	0%	12.08%	20.45%	11.59%	11.59%

5.2 Out-of-sample calibrations

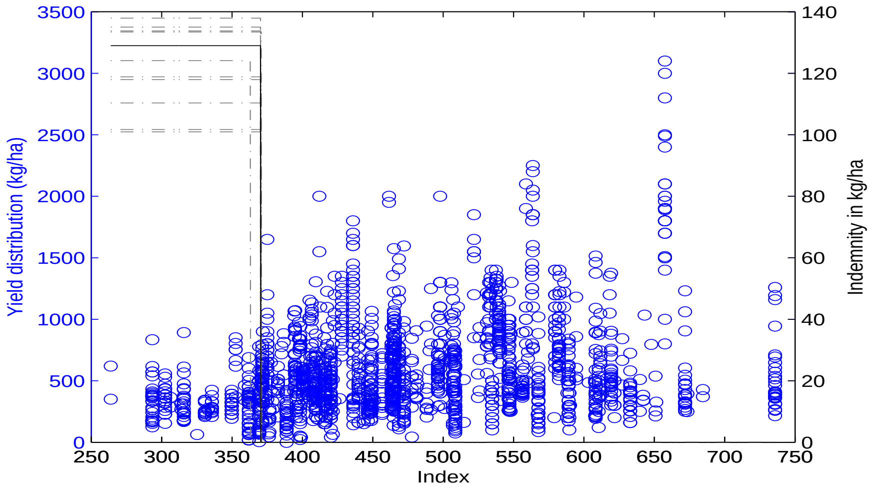

Figure 4: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for CR_{obs} insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

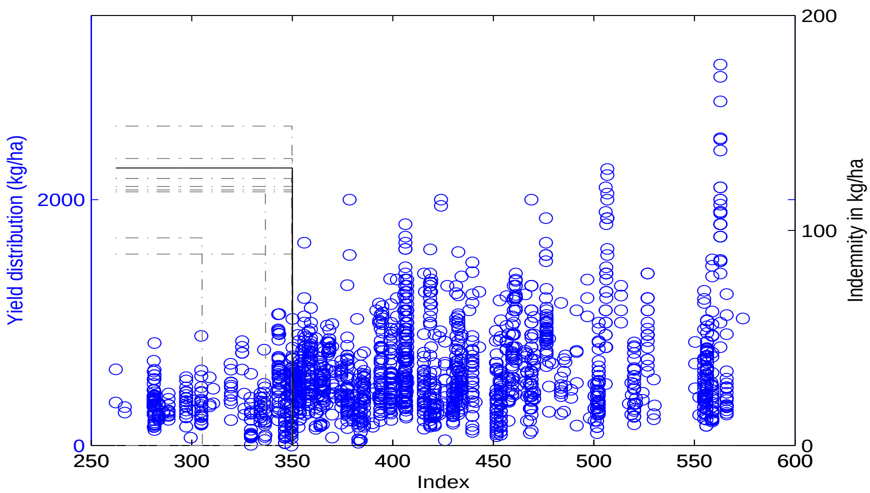

Figure 5: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for BCR_{obs} insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

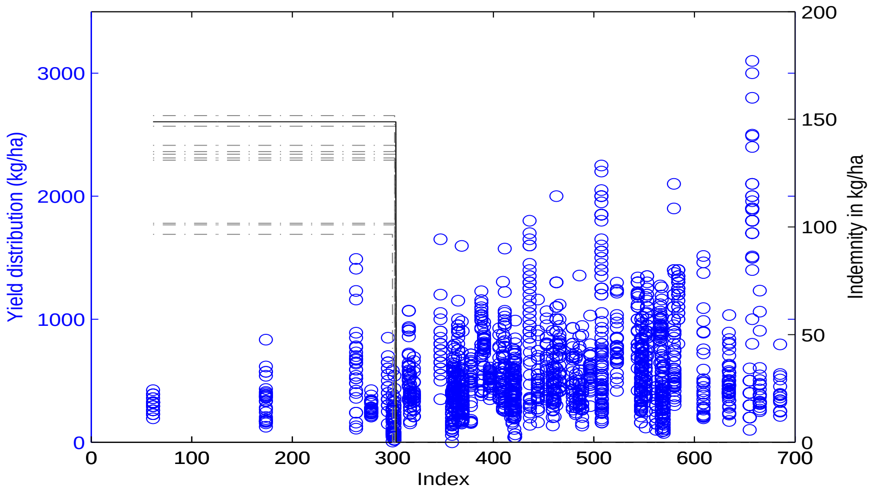

Figure 6: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for CR_{siva} insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

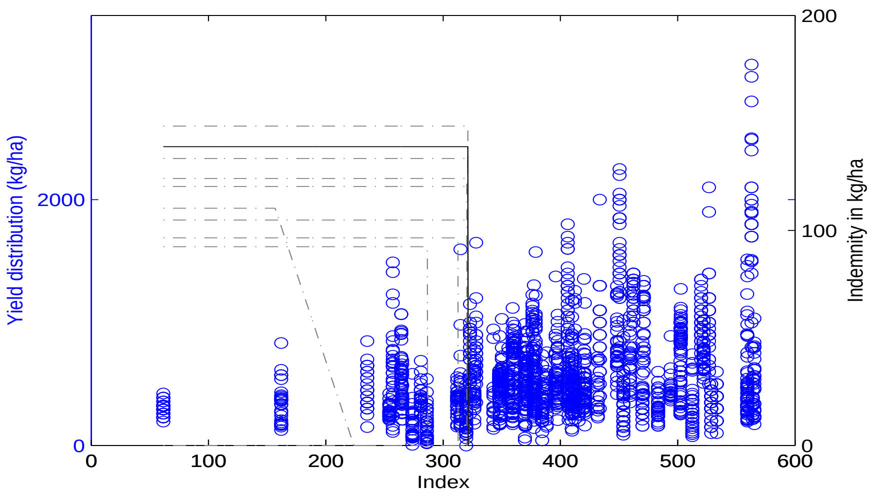

Figure 7: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for BCR_{siva} insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

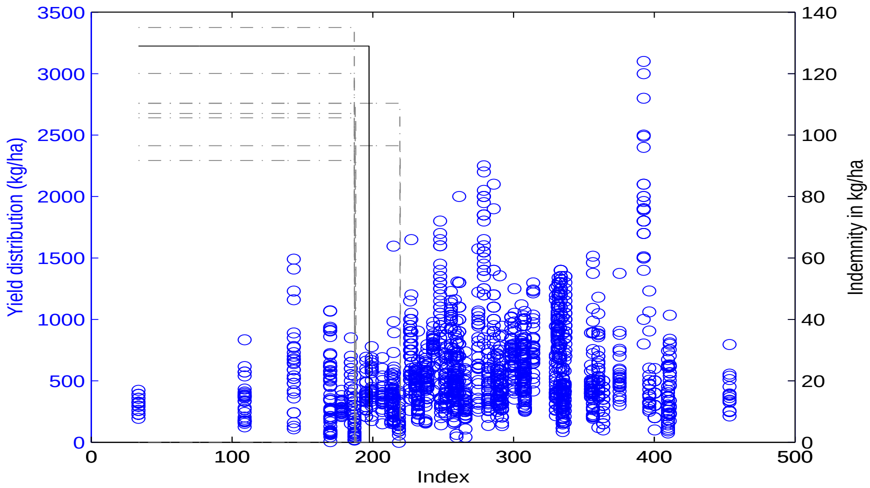

Figure 8: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for $WACR_{siva}$ insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

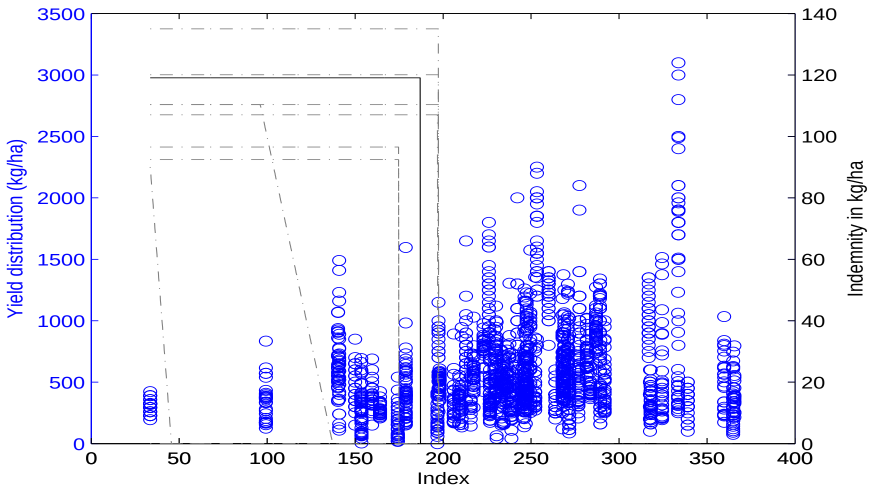

Figure 9: In-sample (solid line) and out-of-sample (dotted lines) indemnity schedules (kg/ha) for $WABCR_{siva}$ insurance, for $\rho = 2$ and scatter plot of yield distribution across index.

5.3 Robustness checks

5.3.1 Prices

We now take the millet cultivation income (plot income summary statistics are displayed in Table 1) for one hectare and compute the CEI gain associated to the distribution of income for the 2004-2010 period. The only difference between Table 3 and Table 12 is that in the latter, we multiplied the yield by the post-harvest millet price, which varies across years. This does not alter any of the results (ranking of index performance, superiority of indices with bounded daily rainfall and superiority of simulated crop cycles) as shown by the comparison of Table 12 with Table 3. The only difference between Table 3 and Table 12 is that we multiplied the yield by the annual post-harvest millet price for the Table 12, the sample and parameters are all the same in each case.

Table 12: Average plot income CEI gain of index insurance.

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
CR_{obs} ins.	.00%	.19%	.90%	1.91%	3.12%
BCR_{obs} ins.	.00%	.24%	1.21%	2.36%	3.71%
CR_{siva} ins.	.00%	.25%	1.10%	2.32%	4.24%
BCR_{siva} ins.	.00%	.25%	1.46%	3.07%	5.15%
$WACR_{siva}$ ins.	.00%	.10%	.78%	1.75%	3.03%
$WABCR_{siva}$ ins.	.00%	.24%	1.43%	3.04%	5.12%

5.3.2 Initial Wealth

Table 13: Average income gain of index insurance

	$\rho = .5$	$\rho = 1$	$\rho = 2$	$\rho = 3$	$\rho = 4$
W_0: **one third of average yield.**					
CEI gain of CR_{obs}-based insurance	.00%	.24%	.94%	1.93%	3.08%
CEI gain of BCR_{obs}-based insurance	.00%	.28%	1.27%	2.40%	3.68%
CEI gain of CR_{siva}-based insurance	.00%	.31%	1.27%	2.62%	4.65%
CEI gain of BCR_{siva}-based insurance	.00%	.29%	1.52%	3.13%	5.21%
CEI gain of $WACR_{siva}$-based insurance	.00%	.16%	.95%	2.06%	3.52%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.23%	1.38%	2.92%	4.95%
W_0: **one sixth of average yield.**					
CEI gain of CR_{obs}-based insurance	.00%	.36%	1.48%	3.23%	5.63%
CEI gain of BCR_{obs}-based insurance	.00%	.47%	1.88%	3.83%	6.48%
CEI gain of CR_{siva}-based insurance	.02%	.50%	2.01%	5.06%	10.01%
CEI gain of BCR_{siva}-based insurance	.00%	.54%	2.45%	5.57%	10.39%
CEI gain of $WACR_{siva}$-based insurance	.00%	.32%	1.59%	3.68%	6.50%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.46%	2.27%	5.32%	10.13%
$W_0 = \big((average\, yield)/1.5\big)$.					
CEI gain of CR_{obs}-based insurance	.00%	.10%	.58%	1.08%	1.69%
CEI gain of BCR_{obs}-based insurance	.00%	.08%	.75%	1.44%	2.15%
CEI gain of CR_{siva}-based insurance	.00%	.12%	.71%	1.41%	2.19%
CEI gain of BCR_{siva}-based insurance	.00%	.05%	.83%	1.71%	2.68%
CEI gain of $WACR_{siva}$-based insurance	.00%	.01%	.47%	1.05%	1.73%
CEI gain of $WABCR_{siva}$-based insurance	.00%	.01%	.72%	1.54%	2.47%

Table 13 shows how modifying the initial level hypothesis alters the results of Table 3, displayed in its first part. If risk premium increases when choosing very low levels of W_0 and large values for ρ, we can say that these results are quite robust regarding this hypothesis since with slight modifications (from 1/5 to 1.5 times average yield) the results are of the same order.

5.3.3 Influence of the period used for calibration

As explained above, our results so far are based on only seven years of data (2004-2010), since yield data are not available for a longer period.

However, weather data are available for a much longer period: 1990-2010. Because of this absence of yield data, we cannot optimize an insurance contract over this longer period, but we can apply over this longer period the contracts optimized over 2004-2010, in order to check whether our optimization period is representative or too specific. With this aim, Figure 11 displays the evolution of the CR_{siva} index during the 1990-2010 period in each of the ten villages. Fortunately, the 2004-2010 period does not show significantly lower or higher values of the index than the longer, 1990-2010 period.

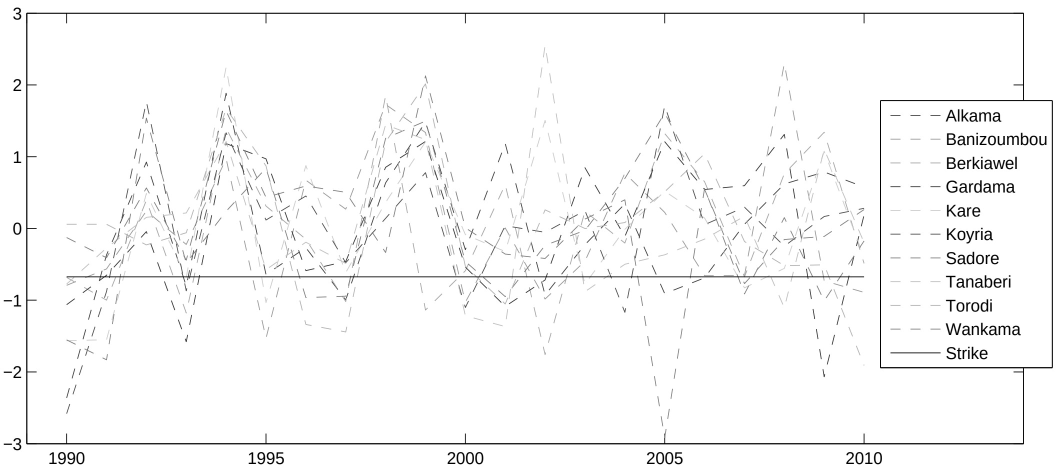

Figure 10: Evolution of the CR_{siva} index during the period 1990-2010: the greyscale represents the latitude; the northern villages are represented in darker grey).

One could also argue that the occurrence of droughts is correlated to locust invasions or other non weather-related events[10]. Such correlation would be a strong issue because it would artificially increase the insurance gain. Fortunately, these damages are reported in the survey we use. We display the correlation matrix between the indices and the non rainfall-related damages in Table 14. Damages are classified in three categories, from the least severe (degree 1) to the most severe (degree 3). Whatever the index, the correlation is lower than 10%, so we are confident that our results are not due to a spurious correlation between drought and locust invasions.

Table 14: Correlation beween non rainfall-related damages (occurrence in percent of plots in a village) and indices.

	Non rainfall-related damages (NRD of degre 3)	NRD (degre 2 and 3)	NRD (degre 1, 2 and 3)
CR_{obs}	-0.050	-0.064	-0.083
BCR_{obs}	-0.044	-0.1055	-0.100
CR_{siva}	0.001	0.0173	0.025
BCR_{siva}	0.01	-0.000	0.029
$WACR_{siva}$	0.037	0.069	0.081
$WABCR_{siva}$	0.045	0.0427	0.076

5.4 Incentive to use costly inputs

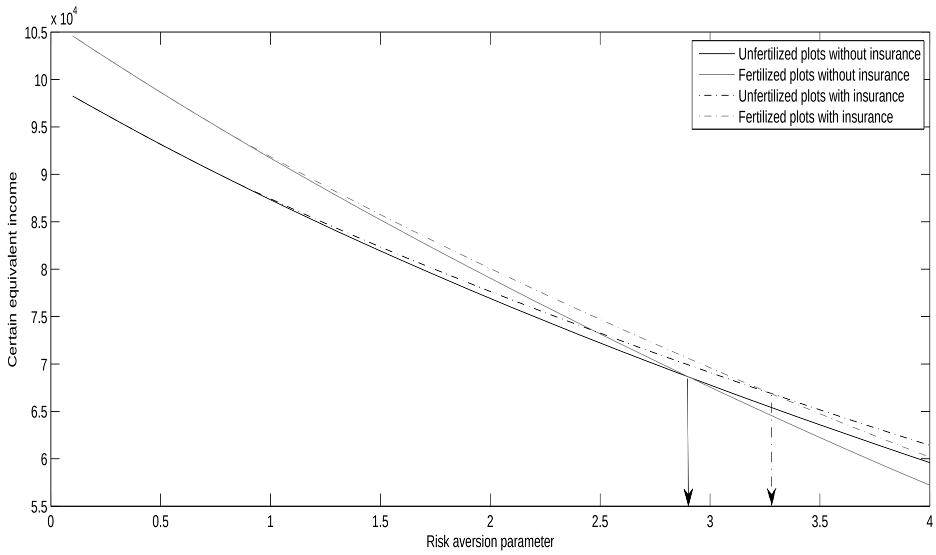

Figure 11: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with BCR_{obs} based insurance (dotted lines), depending on the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income.

[10] We thank an anonymous referee for suggesting this robustness check.

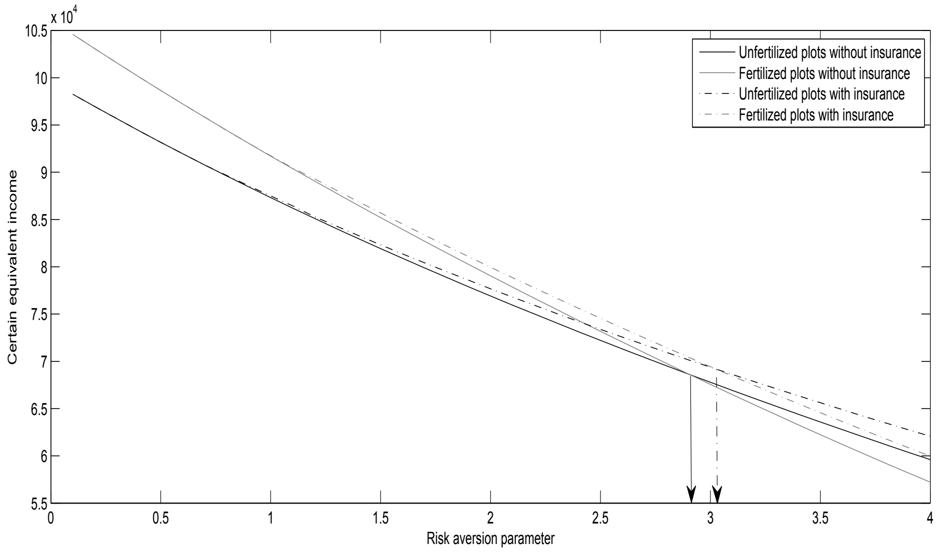

Figure 12: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with CR_{siva} based insurance (dotted lines), depending on the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income.

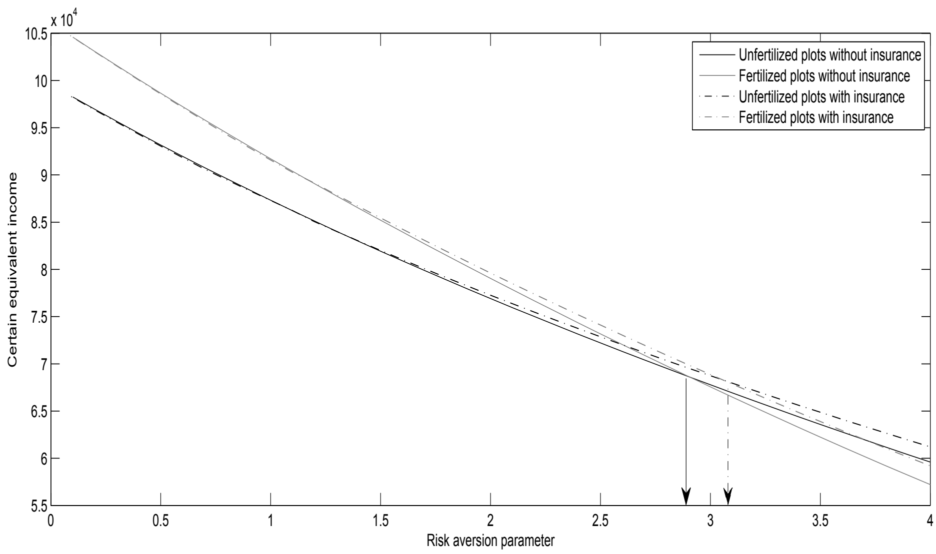

Figure 13: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with BCR_{siva} based insurance (dotted lines), depending on the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income.

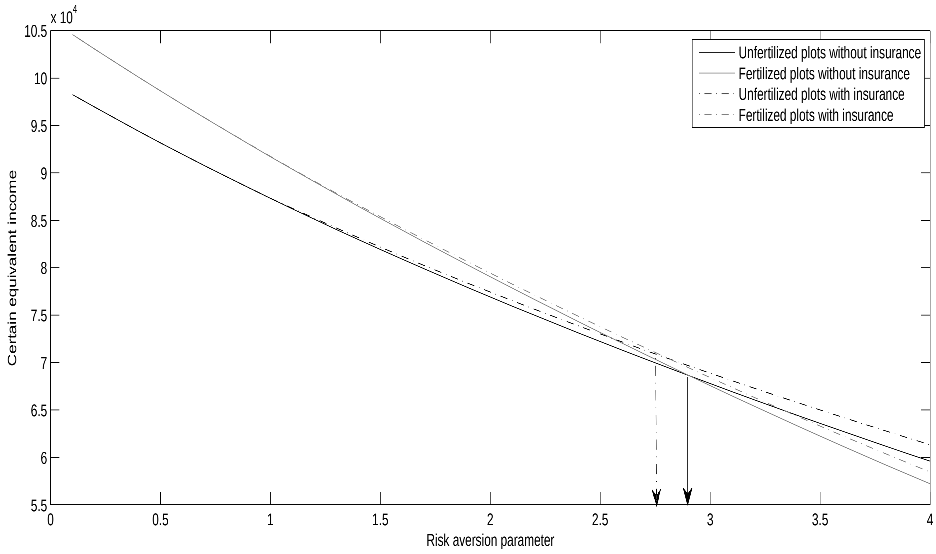

Figure 14: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with $WACR_{siva}$ based insurance (dotted lines), depending on the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income.

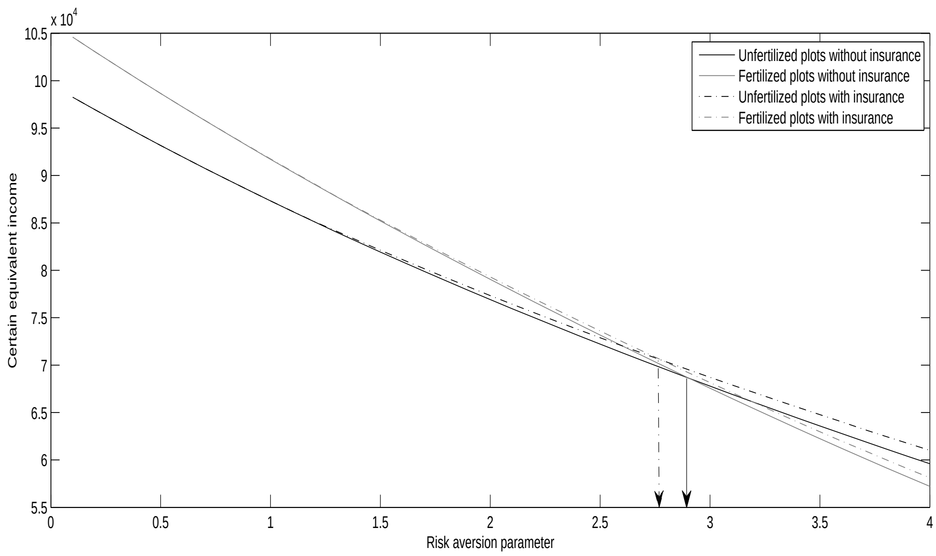

Figure 15: CEI (in FCFA) of encouraged and regular plots without (plain lines) and with $WABCR_{siva}$ based insurance (dotted lines), depending on the risk aversion parameter, ρ and an initial wealth (W_0) of 1/3 of average income.