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Remote sensing data for managing climate risks: Index-based insurance and growth related applications for smallhold-farmers in Ethiopia

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ABSTRACT

The aim of most index-based insurance programs is to act as a social security mechanism and to provide defense against social and financial exclusion for people whose existing coping strategies are failing. For such schemes, insurance payouts do not depend on the individual losses but on an index which serves as a proxy for the losses. As proposed in this paper, also remote sensing data can be used for index-based insurance which gives additional advantages in comparison to traditional on-ground based indexed instruments. Furthermore, distinguishing between a promotion as well as protection level within such schemes is beneficial from a supply as well as demand side perspective and we suggest an approach how both can be simultaneously introduced within a remote sensing index based insurance framework. The applicability and usefulness of the approach is tested for smallhold farmers in North Shewa, Ethiopia. It is found that the use of remote sensing data is indeed a possible alternative to traditional weather based micro-insurance schemes which offers new ways to tackle current problems of such schemes from a supply side as well as demand side perspective.

Introduction

The aim of most micro-insurance programs is to act as a social security mechanism and to provide defense against social and financial exclusion for people whose existing coping strategies are failing (Mosley, 2009). The idea is that if people's livelihoods are protected it would encourage investment among lower-income groups and raise overall investment and growth rates. In other words, micro-insurance should reduce the incidence of "poverty traps" by providing low-income households, farmers, and businesses with access to post-disaster liquidity and securing or rehabilitating their livelihoods and habitations (World Bank, 2009). Moreover, insurance is thought to enhance the creditworthiness of the insured households and farms, thereby promoting investments in productive assets and/or higher-yield crops (Hess and Syroka, 2005).

Farmers especially face a variety of weather, market and production risks that make their incomes volatile from year to year, for example when crops are destroyed by drought or pest outbreaks. These risks are particularly burdensome to the poor, including many smallholder farmers (Carter et al., 2006). In providing a more effective solution in the absence of adequate relief, index-based insurance for agriculture has emerged as a novel mechanism across the globe (Alderman and Haque, 2008). Index-based insurance involves writing contracts against specific perils that are defined and recorded at

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regional levels (usually at local weather stations). For such schemes, insurance payouts do not depend on the individual losses of policyholders but on the regionally recorded index, which serves as a proxy for the losses in a particular region. It is therefore a contingent claim contract for which payouts are determined by an objective index, most of the times weather related parameters (Hochrainer-Stigler et al., 2012). Such parameters need to be highly correlated with farm-level yields or revenue outcomes. In general, rainfall-indexed insurance seems well suited to insure agricultural production in regions where widespread crop losses are caused by drought or excess rainfall. In other areas, farm income can be indexed on temperature indicators for heat or frost sensitive production activities such as horticulture (Mechler et al., 2006). However, as proposed in this paper, remote sensing data can also be used for index-based insurance schemes thereby giving additional advantages in comparison to traditional on-ground based index instruments. For example, they could be applied on the global level without the necessity to have local stations measuring the index. Furthermore, risk spreading over large regions would be possible, which could decrease premium payments considerably (World Bank, 2007).

There are several additional reasons why index-based insurance may serve as an alternative to traditional indemnity based instruments. For example, because payouts for indexed contracts are automatically triggered once a weather parameter reaches a pre-specified level, the insured may receive timely payouts. An automatic trigger also reduces administrative costs for the insurer by eliminating the need for tedious field-level damage assessment. As administrative costs are reduced, premiums may also be lowered and products made more affordable to farmers. Additionally, the objective and exogenous nature of the weather index prevents "adverse selection" (that is, since farmers know more about their risks than the insurer, the low-risk farmers may opt out, leaving the insurer with only high-risk customers) and "moral hazards" (that is, when farmers' behaviors can influence the extent of damage that qualifies for insurance payouts) (see Linnerooth-Bayer and Hochrainer-Stigler, 2014). Indexed products also facilitate risk transfer to the international markets, because international reinsurers are likely to provide better terms when the insurance is based on measurable weather events, instead of farm-level losses.

However, as suggested in this paper, to make index-insurance work, both demand and supply side perspectives must be taken into account (Hochrainer et al., 2010). From the supply side, risk must be quantified in a satisfactory manner (Brown and Churchill, 2000). This is the foremost prerequisite since when risk cannot be quantified, then it is impossible to design an insurance product. Additionally, covariate risk is a chief concern from a supply side perspective as the possibility of large claim payments needs to be addressed (e.g. additional re-insurance must be bought, which can be quite costly in many instances, see Hochrainer, 2006). From a demand side perspective, two pre-requisites are very important. First, there must be interest in insurance and second, premiums must be affordable (see for example the Consultative Group to Assist the Poor, 2003). This is especially important in the context of micro-insurance as premium payments may involve high opportunity costs for the insured, therefore causing other negative consequences such as a decrease in consumption and foregone opportunity to invest in more productive activities (Helgeson et al., 2013).

In that regard, Hess and Hazell (2009) introduced a useful distinction between protection and promotion models for micro index-insurance arrangements that is applied in this article as well. The protection model focuses on protecting people against shock-induced destitution, and provides counter-cyclical safety nets by partially replacing traditional government and international funding for disaster relief and recovery. Under this system, beneficiaries do not pay premiums ex-ante, but may engage ex-post in public works programs. One example is the WFP's food for work programs, in which beneficiaries receive food rations in exchange for participation in programs such as road reconstruction works. The promotion model, on the other hand, promotes increased income and livelihood opportunities by providing access to agricultural credit that may be used to adopt new technologies, improve farming practices and change the risk/return profile of clients. Premiums, which are sometimes bundled with credit provisions, would be paid by beneficiaries. The target group for this type of micro-insurance mechanism is small-holder farmers with some growth potential (Hess and Syroka, 2005).

In this article, we take this idea forward and couple the protection as well as the promotion dimension via the use of remote sensing data within an index-based insurance scheme. The combination of these three aspects has not been explicitly investigated in the micro-insurance and growth literature yet. Our paper should fill part of this gap. The study focuses on Ethiopia, where a large set of new innovative insurance related products, mainly against drought impacts, are currently being tested. While it does not represent a full analysis of all aspects related to index-based schemes, our approach provides a blueprint of how supply and demand side considerations can be taken into account using remote sensing data. Consequently, the application of our suggested approach is therefore not geographically limited and could be applied to any region of the world.

The paper is organized as follows. The "Methodology" section introduces the methodology used for the case study, which is presented in detail in the "Case study area and data" section. The "Results" section presents the results and discusses the limitation of the approach and possible ways forward. Finally, we end with a conclusion and outlook to the future.

Methodology

As discussed at the beginning, index-based insurance uses a proxy for losses and not the losses themselves to trigger claim payments. While usually weather related parameters are employed to create the index, we instead look at remote sensing data as a possible alternative. Furthermore, we distinguish between a protection as well as promotion dimension within an index-based insurance scheme. The protection dimension includes the risk a farmer wants to avoid and is based on the minimum nutrition requirement of a household. The promotion level includes the use of fertilizers to increase crop production. We then combine the information to establish risk levels and insurance needs for small-scale households. The approach is applied afterwards to North Shewa, Ethiopia.

Index–loss relationship

Most index-based micro-insurance products use weather indicators as trigger events for claim payments; however, there is no reason why only weather data can be used as a trigger, and we suggest that remote sensing data such as satellite-based vegetation indices can also serve as a possible index. As indicated, one main benefit would be the possibility to apply the scheme on the global level without the necessity to have local stations measure the index. This could decrease the costs of such contracts and the possibility of default of the insurance pool considerably.

Various remote sensing based indices and combinations could serve as possible predictors for crop yield, probably the most well-known is the Normalized Difference Vegetation Index (NDVI) which is discussed in more detail next. NDVI is known to respond to changes in the amount of green biomass, chlorophyll content and canopy water stress. The relationship between NDVI and biomass production has been long confirmed by field experiments (Rasmussen, 1992; Xianfeng et al., 2012). Karnieli et al. (2010) give a summary of merits and limitations regarding the use of NDVI in drought assessment and generally conclude that its use is more appropriate when water is the primary factor limiting vegetation growth (as in the case of teff, a traditional and very important staple crop in Ethiopia, that is investigated in the case study). Similar to the use of other weather related variables, the general drawback in using statistical relationships between NDVI and crop yield is the small correlation and its solely empirical character (see Liu et al., 2007). For example, no general consensus has been reached as to which NDVI values available during cropping seasons are most important and how such information can be best utilized. The literature is fraught with methodological inconsistencies with some authors using maximum values while others rely on averages, and still others base their analysis on the sum over given lags of NDVI values available in a given cropping season.

The divergent views on NDVI, of course, do not preclude the use of remote sensing data as an appropriate way to assess agricultural production risk. Indeed, considerable focus is currently placed on how satellite based vegetation health indices can be used for drought assessment, and discussions are ongoing as to possible applications in insurance mechanisms (see Rojas et al., 2011). The FAO, for example, has recently investigated how the Agricultural Stress Index System (ASIS) can be coupled with crop insurance, with a trigger defined in terms of a threshold-level Vegetation Health Index. However, the FAO evaluation has so far failed to examine how such an index may be related to premium payments and the level of risk that the insured may want to hedge. This clearly limits the scope of discussion as not only risk reduction but also promotion should be seen as an essential part of a index-insurance scheme. Such combined strategies will be important to make index-insurance products in developing countries a success (Hochrainer-Stigler et al., 2012).

Important remote sensing based data other than the NDVI include the VCI (Vegetation Condition Index), TCI (Temperature Condition Index) and the VHI (Vegetation Health Index). Each of these indices is closely related with the others. For example, VCI index observed at location i over a given time horizon is defined as

$$VCI_i = \frac{100^*(NDVI_i - NDVI_{\min})}{NDVI_{\max} - NDVI_{\min}}$$

the TCI index at location i is defined as

$$TCI_i = \frac{100^*(T_{\max} - T_i)}{T_{\max} - T_{\min}}$$

and the VHI index at location i is the weighted sum of these two indices (w is usually set to 0.5):

$$VHI_i = w^* VCI_i + (1 - w)^* TCI_i$$

Using such and similar indices, one can construct an empirical relationship with regional crop yields (see Hess and Syroka, 2005 for a more detailed application in the case of Malawi). It should be mentioned that there is always the possibility to include other important variables for crop production as well (for example soil moisture) to increase the correlation between the index and the yields. Nevertheless, in this study we focus not on the best model for prediction of crop yields but a satisfactory model to show how, in principle, one can relate remote sensing data (focusing on the above vegetation indices) to index-based insurance.

Protection level

The level of risk a risk bearer wants to avoid is dependent on the level of risk aversion (Malevergne and Sornette, 2005). This information is difficult to gather and usually not at hand (Wang et al., 2011). Sometimes threshold approaches are used to determine if a disaster emanates. For example, Rojas et al. (2011) defines the trigger point for a regional drought as the VHI falling below the 35 value. However, such threshold criteria's are not linked to the actual household situation and therefore not appropriate for insurance purposes as they do not take into account the risk from which the household actually wants to be protected. To overcome this problem and establish a minimum level from which all risk bearers want to be protected, we use the risk of malnutrition based on the minimum nutrition requirements from the FAO. Other threshold levels or dimensions could also be chosen, but hedging the risk of malnutrition can be seen as a lower bound on the question of what kind of risk a farmer definitely wants to avoid. This would therefore give information about the "protection" dimension for an index-based scheme for small scale farmers.

Promotion level

Protection from risk is not sufficient to make insurance products in developing countries attractive, thus we propose that simultaneously an additional "promotion" level be introduced. We focus here on fertilizers, and consequently the promotion level is defined here as a potential increase in growth through the use of fertilizers. To establish the relationship we focus on the so-called Mitscherlich–Baule crop response function (see e.g. Van der Velde et al., 2013), defined as:

$$yld = a_1 * (1 - exp(-a_2 * (a_3 + N))) * (1 - exp(-a_4 * (a_5 + P)))$$

where yld is the yield (ton ha^{-1}) of teff, N the added nitrogen fertilizer, P is the added phosphorus-phosphate fertilizer, a_1 is the maximum yield obtained in each crop trial, a_2 expresses the yield response to the addition of nitrogen fertilizers, a_3 is the residual nitrogen content of the soil, a_4 expresses the yield response to the addition of phosphorus-phosphate fertilizers, and a_5 is the residual phosphorus-phosphate content of the soil. The parameters a_2, a_3, a_4, and a_5 are usually obtained via field trials. In our case-study (see below), we use FAO trials conducted in Ethiopia between 1988 and 1993 as part of the FAO's Fertilizer Programme (for data see: http://www.fao.org/ag/agl/agll/nrdb/; for details on the methodology also see Van der Velde et al. (2013)). To simplify the methodology, only the application of nitrogen based fertilizer is considered (the input of phosphorus, as well as of potassium and micro-nutrients is therefore ignored). The specific parameters were obtained by minimizing the sum of squared errors for all applications in each trial which are located near North Shewa. In more detail, the Nelder-Mead multidimensional unconstrained nonlinear minimization algorithm was used to minimize the objective function (Van der Velde et al., 2013).

Combination of remote sensing data and protection and promotion dimensions

The Mitscherlich–Baule crop response function can be linked to the crop yield and the satellite index, e.g. fertilizer use increases yields which decrease the probability of falling below the minimum nutrition level which is detected via a possible satellite based vegetation index. The different combinations and corresponding risks can be represented via 2 or 3-dimensional mapping. The mapping can then be used to analyze if for a given criteria (e.g. probability of falling below the minimum nutrition requirement level) insurance and/or investment in fertilizer is more appropriate. This decision also depends on the farm size too, but this is neglected in this study as the expansion is straightforward.

Case study area and data

We start with a general description of the most important dimensions for our analysis, e.g. agricultural, farm, weather and disaster related ones. Ethiopia's agriculture is dominated by small farms who cultivate mainly cereals for own-consumption and sales (Taffesse et al., 2010). Major staples are barley and teff, but also sorghum, chick pea and wheat are grown. Teff accounts for 28% of the total cereal area, while maize stands for 27% of total annual cereal production. In terms of acreage, pulses are the second most important crop after cereals, with the third most important crop group being oilseeds. Coffee is a major cash crop accounting for 3.8% of GDP, but occupying only 2.7% of total area cultivated.

The Central Statistical Agency (CSA) classifies Ethiopian farms into two major groups: Smallholder "peasant" farms, that cultivate less than 25.2 hectares and large commercial farms with an average of 323 hectares per farm. Around 60% of the small farms cultivate less than 0.9 hectares of land and 40% of these farmers cultivate less than 0.52 hectares. Small farms produce mostly for own-consumption and generate only a small surplus that is sold in the market. The agricultural production is spread across different agro-ecological regions. Most small hold farms are located in the moisture reliable cereal-based highlands, which account for 50% of all farm area. Farmers in the humid lowlands and pastoralists account for around 3.9% of all smallholders in Ethiopia. There are approximately 47 million small ruminants, of which half are sheep and the other half goats. Both are integral part of mixed farming systems in most parts of the country (Legesse et al., 2008).

Regarding the climate in Ethiopia, three seasons can be distinguished: The *Bega* or dry season (from October to January), the *Belg* or short rainy season (from February to May) and the *Kiremt* or long rainy season (from June to September). Rainfall is very important as more than 95% of the arable land is cultivated without irrigation (Araya and Stroosnijder, 2011). About 70–80% of the rain falls in the *Kiremt* season. The growing period starts in early July and ends in early to late September, with a rainy period of a maximum of 80 days.

Most of the drought and food crises events are concentrated in two broad zones of Ethiopia (FAOSTAT, 2009). The first consist of the central and northern highlands, stretching from northern Shewa through Wello and Tigray, and the second consists of low-lying agro-pastoral lands ranging from Wello in the north, through Hararghe and Bale, to Sidamo and Gamo Gofa in the south (Gebrehiwot et al., 2011).The specific study region analyzed here is North Shewa, one of 10 zones in the

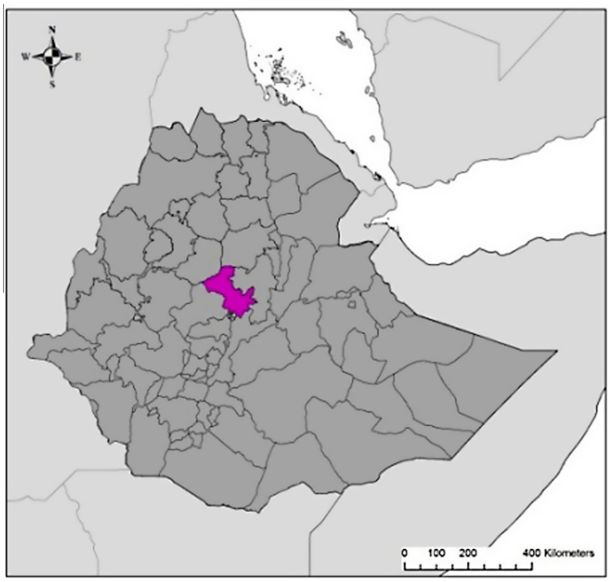

Fig. 1. Study region in Ethiopia.

Ethiopian Amhara region, being very exposed to droughts (Fig. 1). The dominating land cover type is cropland with more than 90% of the province used for agriculture proposes. The remaining land is covered by shrubs.

Teff is the main staple crop and principal source of carbohydrates for the majority of the population there. It is a drought resistant crop adapted to the dryland farming environment, however, among others, water shortage is one of the major yield limiting factors. Teff is normally sown at the peak of the rainy period, which in North Shewa is from around the third week of July to the first week of August (USDA, 2009). There is no *Belg* season in the region, so it is normally dry for nine months from September up to the next June. North Shewa is important from a poverty reduction perspective with sufficient data to proceed with the proposed modeling framework, and therefore serves as a good case study region for our analysis.

The data used includes crop yield data from the International Food Policy Research Institute IFPRI (2008), which provides crop yields in tons per hectare per year for each zone shown in Fig. 1 for Teff and other relevant crops between 1996 and 2005. NDVI data was taken from the GIMMS (Global Inventory Modeling and Mapping Studies) data set spanning from 1981 to 2006 in a 8 km GRID resolution. The data set is derived from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the NOAA satellite series 7, 9, 11, 14, 16 and 17. This is an NDVI dataset that has been corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation change. The GIMMS collection is available in two projections: Albers projection with each continent a separate file or global files in Geographic coordinates (for more details see also http://glcf.umd.edu/data/gimms/index.shtml or http://phenology.cr.usgs.gov/ndvi_avhrr.php). Daily temperature was taken from the SLATE (Synthesized Long-Term Weather) dataset v.1.1 (HarvestChoice, 2011) that covers a 100 year period from 1910 to 2009 for sub-Saharan Africa at a 0.5° spatial resolution. The SLATE dataset is a synthesized combination of actually two databases, CRU-TS and NASA POWER. The University of East Anglia CRU-TS is a historic time-series climate database with monthly mean of climate elements (cloud cover, diurnal temperature range, frost day frequency, precipitation, daily mean temperature, monthly average daily minimum and maximum temperatures, vapor pressure, and wet day frequency) over the global land area. Version 3.1 of the CRU-TS covers the time period from 1901 to 2009 at 0.5° spatial resolution. The database uses available station records and interpolation methods. NASA POWER, (the Prediction of Worldwide Energy Resource), is a NASA database and provides satellite-based estimates on surface meteorology and solar energy since 1997 at 1° spatial resolution. POWER provides all the climate elements that crop models typically require, including solar radiation, daily temperature minimum and maximum, and rainfall. Since the methodology is built upon a series of assumptions, it cannot be regarded as real data, however, the outcome of this process is plausible enough to be used in a modeling exercise such as this one (see for more details http://harvestchoice.org/labs/2010/08/cru-mashup/%2523100_years_of_daily).

Results

Index construction

We start with the establishment of the index-yield relationship by comparing crop yield data for teff with the Vegetation Health Index (VHI). In a first step, to de-trend the yield increase due to increases in cropping area and also to relate crop production with household characteristics, total crop production was divided by total cropping area in a given year to arrive at crop yield estimates in tons per hectare for the respective time horizon. As discussed, NDVI data was taken from the GIMMs dataset which includes NDVI values from 1981 to 2006 in 15 day periods. Daily temperature data was taken from the SLATE dataset, which provides data from 1910 to 2009 at 0.5° spatial resolution (HarvestChoice, 2011) and aggregated to 15 –day periods. Both were taken to calculate the corresponding VHI values. Fig. 2 shows the mean VHI over the last 30 years for these 15 day periods for North Shewa.

According to the crop calendar (FAO/GIEWS, 2002) for teff, the cropping season is starting around Block 10 (May) and harvest takes place around Block 20 (end of October). This is also reflected within Fig. 2. Various regression models were applied to detect the best fit between crop (teff) yield and the VHI index. For example, the VHI values for each block (as well as the squared numbers to incorporate possible non-linearities) and maximum and minimum values over the 15 day blocks were used (together with their squares) to estimate a VHI-yield function in the form of:

$$Y = \beta_0 + \sum_{k=1}^{n} \beta_k X_k + \sum_{l=1}^{m} \beta_l X_l^2$$

where Y is crop yield (t/hectare), β represents the coefficient parameter of the regression model and X represents independent variables, e.g. VHI or NDVI as well as Temperature indices. A highly significant model ($F = 10.151$, $df = 8$, $p = 0.015$) was found if the VHI of block 17 (middle of September) is used. A total of around 60% of the variability can be explained with this variable alone. While a real-world index-based product could not be constructed using just this variable (usually, for index-based insurance products the index should explain at least 80% of the variability), it nevertheless serves our purpose in demonstrating the applicability of the aforementioned approach. Hence, we use this relationship for our case study. The estimated model can be stated as

$$\text{Yield(ton per hectare)} = -2.710 + 0.042^{*} VHI\_\text{Block\_17}$$

The VHI values for block 17 from 1981 till 2006 were afterwards used to estimate a Gumbel distribution. The Gumbel distribution was chosen as it reflects both very negative and very positive outcomes (of VHI and therefore crop production). Using this distribution additional crop yields can be simulated for determining premiums (e.g. via Monte Carlo simulation using the inverse transformation method). However, this has to be based on the actual risk from which the risk bearer may want to be protected, which is therefore discussed next.

Crop yields, risk and protection

Our task is to quantify the risk that a household falls below the minimum nutrition level in a given year. Around 60% of the small farms cultivate less than 0.9 hectares of land and 40% of these farmers cultivate less than 0.52 hectares. We are especially interested in the small household farmers with some growth potential and focus on a typical household with 0.9 hectares of land. The average household size in this area is around 4.5 persons (UNFPA Census, 2007). Hence, we choose the number of small scale farmers' household size to be 5, assuming 2 working adults, and 3 children. The average energy requirement at rest for an average man (70 kg between age 30 and 50) is estimated to be around 1700 kcal or 7000 kJ a day (Faller et al., 2004). The FAO (2010) estimates the minimum dietary energy requirement for Ethiopia at around 1740 kcal per

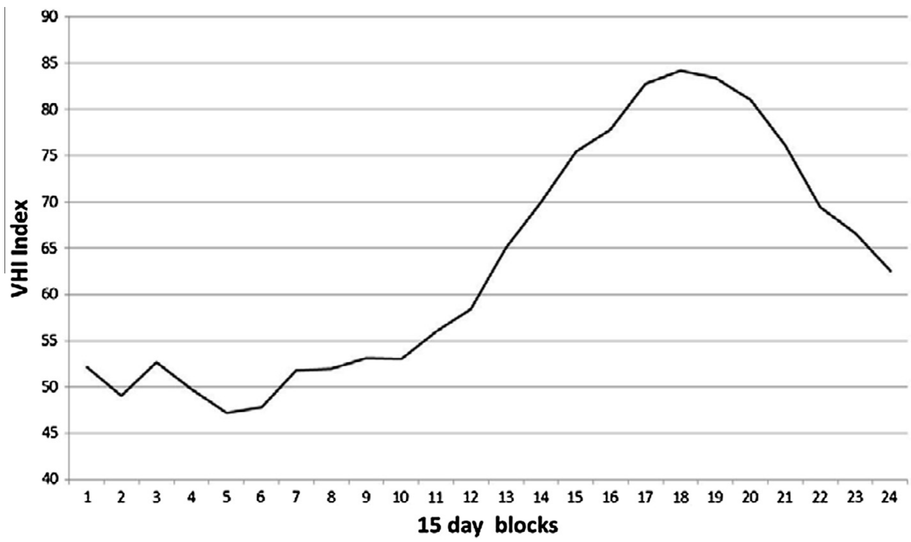

Fig. 2. Average VHI values for North Shewa in 15 day blocks starting in January (Block 1) to December (Block 24).

day. For simplicity we set the minimum energy requirement to be 1800 kcal or 7500 kJ per day for an adult. Also, we assume that for children the calorie requirement is half that of adults. Therefore, the annual minimum energy requirement for the respective household is around 2.3 million kcal or 9.6 million kJ. Now, let's assume that from teff a total energy of 1468 kJ per 100 g can be used (Dijkstra et al., 2008; see also Brink and Belay, 2006). Accordingly, 1 kg of teff contains around 14,680 kJ of energy and 1 ton of teff contains 14.8 million kJ. Given these reflections, the question about the risk of falling below the minimum requirement can now be addressed quantitatively.

We use a Monte Carlo Simulation technique to simulate VHI of block 17 and calculate a corresponding yield curve based on the empirical relationship identified in the previous steps. As said, to include behavior for extreme cases (high and low yields), again a Gumbel model is used (Maximum Likelihood techniques are employed; for 0.9 hectare the parameters are estimated at 0.6827 and 0.1462, respectively). For a small scale household with 0.9 hectare of land, the probability that it will fall below the minimum energy requirement of 9.6 million kJ per year is around 55%. Now, assume that the difference between the crop yield and the minimum energy requirement will be provided via an insurance mechanism (if the crop yield is above the threshold than there is no provision). The corresponding expected annual payments (here in tons of teff) would be with this arrangement around 0.095 tons. Assuming an average price of teff to be around 700 USD per ton (however, large fluctuations have been experienced in the past and teff prices are expected to increase), this expected transaction would be worth approximately 67 USD. The estimated expectation can also be seen as the actuarial fair price, i.e. under the assumption of no premium loadings. Using this type of insurance contract, the risk of malnutrition will be reduced for small farms, however, such insurance may not be necessary for larger farms, since every farmer who has more than 25.2 hectares (threshold for the two types of farmers, i.e. peasant and large farms) has less than 1% chance of falling below the minimum nutrition requirement level.

Promotion

As indicated, we use FAO trials near our case study to estimate the Mitscherlich–Baule crop response function. These may be conservative estimates, since the information was gathered over 20 years ago, however, we proceed with the following analysis given that no better information is currently available and our estimates can be assumed to be lower bounds of growth (see also the discussion section). Twenty-one (21) trials with at least 5 different nutrient input levels have been selected and they show a reasonable relation between nutrient inputs and yields (Fig. 3, Table 1).

Note, the function was also re-calibrated to past average teff yields within the case study during no drought events (Dijkstra et al., 2008). To simulate a drought event, we decreased the crop yields according to our regression function and this was also kept the same for the Mitscherlich–Baule crop response function. Furthermore, as the crop yields and the VHI index are directly related, it is also possible to define the trigger event without any problems in all cases (as satellite indices are based on real observations). Hence, for different farmers with different inputs, such as fertilizer use and crop yield risks, the risk of falling below the minimum nutrition requirement level can be directly calculated via the VHI.

Regarding fertilizer costs, they can be considerable with all sorts of problems (for example, they are only sold in 50 kg bags, see for a discussion Spielman et al. (2011)). To have a close relationship with the Mitscherlich–Baule crop response function, we use as specific fertilizer "Urea" (it has 46% of N nutrition). The current international price for one ton of Urea is fluctuating but set here to be 388 USD (Spielman et al., 2011). As said, half of it is N (see Gregory and Bumb, 2011), i.e. 500 kg N per ton of Urea. Hence, 1 ton of N costs 776 USD, or 1 kg costs 0.776 USD.

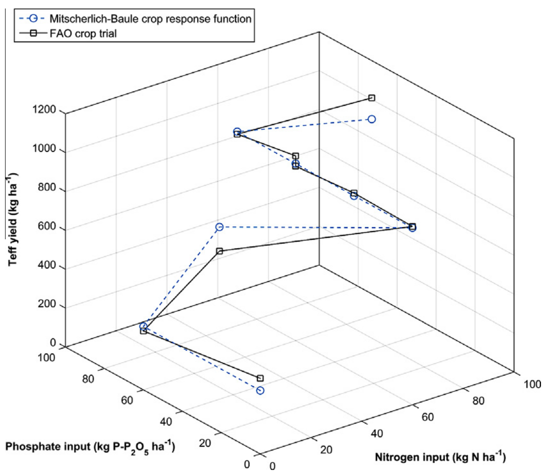

Fig. 3. An example of data from a teff fertilizer response FAO trial (black squares) and the corresponding Mitscherlich–Baule crop response surface (blue circles). Corresponding Table 1 shows the estimated parameters of the crop response function near the test site case. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Mitscherlich–Baule crop response function.

Parameters
$a_1 = 2507$ (kg)
$a_2 = 0.0220$
$a_3 = 15.5878$
$a_4 = 0.2305$
$a_5 = 98.1479$

Risk financing and growth

Given that a small scale farmer has 0.9 hectares of land that can be used to grow teff, how much should he invest in fertilizers to decrease the probability of falling below the minimum nutrition level to, say, 5%? Our previous analysis showed that the insurance premium would cost at least 67 USD (in this case, the farmer is safe in the case of all events that lead to crop yields below the minimum nutrition level). An optimization algorithm can be applied to find out that a farm investing in at least 40 kg of N fertilizer per year would decrease the annual probability of malnutrition from 55% to 5%. This is equivalent to an investment in 80 kg of Urea per year, which costs approximately 62 USD. Observe, the fertilizer is not only decreasing the risk of malnutrition but also the average crop yields. In comparison to the insurance premium calculated above, fertilizer use seems to be a very cost effective risk reduction as well as growth instrument. This can be illustrated further using Fig. 4 and the VHI index representing the risk of malnutrition (the main reason for using VHI here instead of the yields is that, in our case, the actual observation of crop yields will not be available and therefore the focus is on the remote sensing based indicator). Recall, the VHI index is a distribution function which also can be used to estimate the probability of malnutrition. This is possible because of the established relationship with crop yields. Using fertilizers, through the Mitscherlich–Baule crop response function the crop yield distribution will be shifted to the right, and consequently the probability of malnutrition is decreased as well. Due to the one-to-one correspondence of the crop yields with the VHI index, also the VHI index could be seen as shifted. Hence, also the VHI index can be used for representing the risk of malnutrition. For example, according to Fig. 4, with no fertilizer use a VHI value below 85 would indicate malnutrition, while using 40 kg fertilizer would shift the VHI index distribution (via the crop index relationship) so that malnutrition (with 5% chance) would occur now only if VHI is below 73 in the new VHI distribution.

Fig. 4 can also be viewed the other way round, i.e. comparing the risk to malnutrition to the no fertilizer use case: if VHI is kept constant at the 85 VHI level, the use of fertilizer decreases the chance (probability) of malnutrition (e.g. number of red squares decreases). The marginal decrease in red squares (representing malnutrition) is quite steep at the very beginning indicating the high efficiency of fertilizer for small amounts used. Fig. 5 presents this relationship between crop yields, fertilizer use and VHI index in more detail.

Consequently, the promotion part in this case is very important and can decrease costs for the protection level considerably. Let's assume that 80 kg of fertilizer is now used and let us calculate what an insurance product as discussed above would now cost (in terms of fair premiums) if only the remaining 5% risk of malnutrition should be hedged. Again using the simulation approach described above, one would find that the premium now would cost 19 USD (in comparison to 67 USD). Total costs for fertilizer use and insurance would be then 62 + 19 = 81 USD. In this way the risk of farmers would be decreased considerably while crop yields are (on average) more than doubled. Consequently, from a demand side perspective an index insurance product that enables farmers to obtain credits for fertilizer use protection against malnutrition seems attractive. For example, a field experiment by Hill and Viceisza (2012) found that insurance has a positive impact on

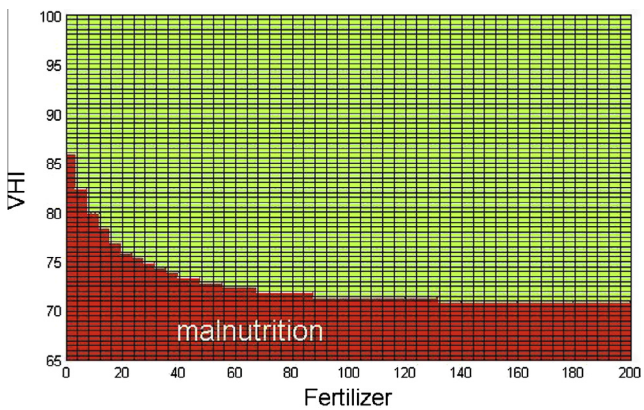

Fig. 4. VHI as risk indicator, fertilizer input and malnutrition points.

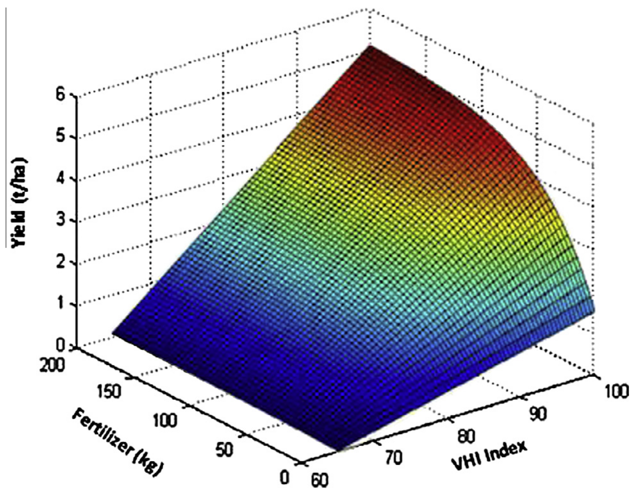

Fig. 5. Crop yield responses in combination with VHI indices and fertilizer combinations.

fertilizer purchases, while still depending on wealth and (in accordance to the law of small numbers) past history of weather realizations. From a supply side perspective, the credit can be coupled to the VHI index, which, if triggered, would pay the bank the credit back (as in this case, the farmer will not be able to do this as he is already in a difficult situation, see as a possible application the index-insurance scheme in Malawi, Hess and Syroka (2005)), and would help the farmers to stay above the minimum nutrition requirement level. The index itself is observed via remote sensing data and therefore costs should be small with all the benefits of the index-based insurance products discussed above. Furthermore, as this can be applied on the global level, risk spreading, especially important for extreme events, can be achieved in an effective manner.

Limitations and way forward

In Ethiopia, the use of fertilizers and improved seeds are the main yield-increasing investments available for crop farmers. However, while investing in fertilizer increases yields substantially under ample rain, it has little effect under insufficient rainfall. Regarding the latter, we did not explicitly included the decrease in yields due to severely insufficient rainfall in our model. As a consequence, the results are overoptimistic in the case of severe droughts as the change in crop yields would not be as high as the Mitscherlich–Baule function would predict. The occurrence of droughts and associated production risks is of course also a major reason for the aversion of farmers to invest in fertilizers. Nevertheless, these results should be valid for moderate drought events. For example, Araya and Stroosnijder (2011) estimated crop coefficients and yield responses due to water stress for teff in Ethiopia and found that yield is dramatically reduced when optimal water amount is not applied at the early establishment and flowering stage. However, teff yield was found to respond almost linearly to the amount of water applied and then to form a plateau over a larger range of supplementary irrigations. The seasonal yield response to water stress factor was estimated to be 1.04, which indicates a moderately sensitive and linear response to water stress. Especially the potential for yield improvement seems to increase under lower rainfall; hence, possible combinations of water conservation farming, fertilizer use and crop micro-insurance as discussed here could be especially beneficial for small scale farmers.

Furthermore, the oversimplistic statistical representation of the VHI and crop yield relationship is problematic if used for real-world application and there are various possibilities to increase the fit of the model if needed. For example, one could additionally use satellite-derived soil moisture data to bridge the gap between atmospheric process and land surface interactions (Legates et al., 2010). In that way, more variation of crop production can be explained and therefore "basis risk" reduced, i.e. the probability that a loss occurs but the index is not triggered. One other way to decrease basis risk is to couple satellite-derived data with on-ground observations, for example via local weather stations or crop yield samples from selected farmers in a given region. Additionally, one has to assume some error within NDVI and related datasets due to atmospheric noise etc. (see for example Dinku et al., 2007; Thiemig et al., 2012). In that regard, one could apply new noise-corrected and gap filled datasets that are sometimes available operationally even at the 250 m scale (Vuolo et al., 2012). Also, the sustainability of the insurance scheme may be threatened by climate change and therefore has to be adapted on a continuous basis (Hochrainer-Stigler et al., 2012). Given the importance of phosphorus for African crop production (Van der Velde et al., 2014), our approach could be extend to cover phosphorus fertilizer inputs as well. All of the suggestions are valid, however, it has to be noted that they can greatly complicate the process of calculating premiums and may be inappropriate due to data scarcity. Even more important, more complicated models could decrease farmers' understanding and trust in the insurance system, which is essential from the demand side perspective (Patt et al., 2010).

In our analysis we only looked at teff and neglected the possibility to plant other crops as well, especially cash crops. While this is a minor issue for the small-scale farmers it still is heavily discussed as a promising alternative. It should be noted that farmers not only care about the productivity (of the crop varieties) but also about environmental adaptability and yield stability (Asrat et al., 2010). In countries like Ethiopia, where crop production is mainly rain fed and is subject to natural calamities, production risk is an important consideration when making planting decisions. Under a challenging production environment, farmers' reliance on crop biodiversity is indeed very important. The level of rainfall and household land endowments tend to govern crop diversity decisions, and the choice of a number of crop species is found to be correlated with rainfall in its lagged and current levels (Di Falco et al., 2010). When farmers expect harsher environmental conditions, they use more diversity to reduce the risk of crop loss and maintain productivity of their agro-ecosystem. These linkages between consumption risk, technology adoption, and poverty traps were the focal point of the study from Dercon and Christiaensen (2011). They found that in the anticipation of possible negative covariate shocks, households, especially poorer ones, opt for less risky technologies and portfolios in order to avoid permanent damage. Fertilizer application rates were also found to be lower due to downside risk in consumption (see also Hill and Viceisza, 2012).

In that regard, the link between downside consumption risk and modern input adoption suggests that risk may be an underlying cause of perpetuating poverty: those poorer households that are unable to protect themselves against downside risk are forced to avoid it by reducing the use of profitable modern inputs. As such, risk can be seen as a cause of persistent poverty for some, as they are trapped in lower risk yet lower return agriculture production. In such cases, micro-insurance may offer a potential way out of poverty. As said, there are positive indications, such as the field experiment by Hill and Viceisza (2012), which found that insurance has a positive impact on fertilizer purchases (see also Gregory and Bumb, 2011). Tadesse and Brans (2012) also identified that low income households need and would be willing to buy insurance if it would be widely available. While risk averse borrowers may prefer planting a traditional variety that does not require credit, for the adoption of a riskier variety, the provision of insurance should in principle raise the adoption rate among them. This hypothesis is not always verified within empirical studies, as, for example, Giné and Yang (2009) found opposite effects of micro-insurance and explained that the bundling of a loan with formal insurance effectively increases the interest rate on the loan. However, in most studies insurance was found to be an interesting option even for the poor, and fertilizer use was seen as an accepted way to achieve growth (see for a summary Hochrainer-Stigler et al., 2012).

Indicated already at the beginning, as remote sensing data is basically available for all parts of the world, such indices would have the potential to create global insurance pools that could diversify risk effectively over the globe and therefore could decrease premium payments to affordable levels. However, agricultural productivity is crop specific and therefore needs to be based on on-ground data. New crowd sourcing activities suggest that citizen science may be a promising way forward to derive at these datasets on a global level within a reasonable time frame (Fritz et al., 2009, 2012). The additional linkage of satellite based data to a protection and promotion dimension seems beneficial for many reasons, including demand side (e.g. risk reduction and growth possibilities) as well as supply side (e.g. risk spreading and low costs) perspectives.

Conclusion

We presented an approach in which remote sensing data was used to design index-based insurance arrangements for small household farmers in a developing country taking explicitly protection as well as promotion dimensions into account. It is argued, given that a satisfactory relationship between indices based on remote sensing data (such as the VHI) and crop yield responses is established, it is possible to identify trigger points for claim payments, as is typically done with weather station based index-insurance products. With the proposed method, it is also possible to calculate premiums or fertilizer needs reflecting the specific risk profile of individual households. The proposed framework also incorporates the possibilities to use production strategies (here through fertilizers), instead of risk hedging only. The proposed remote sensing data based micro-insurance scheme offers a promotion and protection level, and therefore can be seen as a possible alternative to traditional index-insurance products.

It should be noted that satellite-observation data as used in this study was recently applied in a number of rural settings in Ethiopia (however not for insurance purposes). For example, the spatial and temporal variability of drought was evaluated by Gebrehiwot et al. (2011) in Tigray. Based on remotely sensed images and precipitation data such as the standardized precipitation index (SPI), the normalized difference vegetation index (NDVI) and the corresponding vegetation condition index (VCI), significant correlations were found suggesting that VCI indices can be used to analyze the drought status at a regional scale. Additionally, VCI may be used to identify the spatial diversity of drought conditions across large areas, offering the possibility for early prediction of droughts thereby improving drought risk management. Tonini et al. (2012) used an extreme value approach to develop a so called Absolute Difference NDVI (ADVI) metric to assess the risk of drought events in the south Tigray. Their study focused on negative shifts of ADVI to determine extreme negative precipitation scenarios that can be used for drought monitoring.

Our study should fill part of the gap on how rural risk reduction and growth objectives can simultaneously be pursued within an index-insurance framework, while satisfying both supply and demand side considerations in combination with the help of remote sensing data. However, further issues must be addressed to make this framework operational. First, the correlation between VHI index and crop yields has to be established in a satisfactory manner, i.e. it would be ideal if at least 90% of crop yield variation can be explained via such indices. Second, the relationship between fertilizer use and VHI data has to be analyzed further. In this study, we adopted a simplified version in which the possible interaction of fertilizer use and water availability was not included. The existing studies have shown that the relationship between crop yield and water availability is more or less linear for teff, however, whether this is also the case among VHI and teff yields in combination with fertilizer use has to be empirically examined. Third, as individual farmers have different levels of initial assets, such as farm size, fertilizer use, and also savings, it is necessary to perform a more detailed analysis from a livelihood perspective as a next step calculating the opportunity costs of insurance and/or use of fertilizers. Such consideration is especially important as small farms typically have meager resources to afford these options and some form of assistance such as subsidized products may be necessary. The present analysis also neglected issues arising from non-market functions or the complete absence of markets, which is the case for insurance as well as fertilizers in the study area. How such market specific barriers may be addressed should be researched further, but a global index-insurance pool could be a more promising direction than large amounts of small pilot projects. Price uncertainty due to general commodity price volatility and drought situation should also be examined. As illustrated in the present study, risk promotion is as important as risk reduction since farmers should have the possibility to avoid risk and to move out of poverty traps by investing in growth opportunities. Without an additional dimension of risk-taking, it is unlikely that insurance products will be beneficial and successful in the long run. In that regard, the use of remote sensing data offers a new avenue for integrated, pro-growth index-based insurance strategies. Last but not least, possibilities for a global pool would further decrease premiums and may be an important next step for hedging climate risk around the world. Current investigations such as those in Rojas et al. (2011) could be in principle easily extended to insurance related applications with similar approaches as described in this paper.

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