

Supplementary information

Uniting remote sensing, crop modelling and economics for agricultural risk management

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Supplementary Information for:

Uniting Remote Sensing, Crop Modelling and Economics for Agricultural Risk Management

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S.1 Quality measures elaborated

A simple example can illustrate the intuition of the minimum quality measure described in the main manuscript. First, suppose a farmer faces two possible outcomes—a high income state (y_h) and a low income state (y_ℓ). Second, consider an index insurance contract based on satellite data that either pays out a fixed amount ($I_p = I$) or pays nothing ($I_n = 0$). Finally, denote the probability that income j occurs with payout k as ϕ_{jk} . That is, $\phi_{\ell n}$ represents the probability that the insurance contract pays nothing in the low income state and ϕ_{hp} that the insurance contract pays I in the high income state. If the insurance contract works perfectly, $\phi_{\ell n} = 0$ and $\phi_{hp} = 0$. However, with prediction errors, we would expect both probabilities to be strictly positive, i.e., the contract payouts include false negatives ($\phi_{\ell n} > 0$) and false positives ($\phi_{hp} > 0$). False negatives make a farmer even worse off for having insurance than without, as the farmer pays a premium (π) to have insurance but doesn't receive a payout when hard times fall and money is scarce ($y_\ell - \pi < y_\ell$).

To measure an individual's level of subjective well-being, economists typically employ a concave function that maps income to subjective well-being. This “utility function” ($u(y)$ with $u' > 0, u'' \leq 0$) captures the idea that a dollar matters more to people they are poor and desperate than when they have more income ($u'(y_\ell) > u'(y_h)$). Where $\phi_\ell = \phi_{\ell n} + \phi_{\ell p}$ reflects the probability that the low income state occurs, we can express the expected level of well-being for an uninsured individual as $EU^N = \phi_\ell u(y_\ell) + \phi_h u(y_h)$ and use a similar equation but with premium payments (π) and indemnity pay-outs (I) for an insured individual:

$$EU^I = \phi_{\ell n} u(y_\ell - \pi) + \phi_{\ell p} u(y_\ell - \pi + I) + \phi_{hn} u(y_h - \pi) + \phi_{hp} u(y_h - \pi + I)$$

If we measure the value of insurance as the difference between the expected utility with and without insurance (i.e., $EU^I - EU^N$), we can reduce the above expression to a function of the three key elements:

$$Q = \sum_{j=\ell, h} \left(\sum_{k=p, n} (\phi_{jk} \lambda_j \Delta_{jk}) \right)$$

where $\Delta_{jk} = (y_j - \pi + I_k) - (y_j)$ reflects the income difference with and without insurance, and $\lambda_j \equiv u'(y_j) > 0$ reflects the farmer's desperation¹ when income is at level j , indicating a dollar is more valuable in bad states (y_ℓ) than good states (y_h): $\lambda_\ell > \lambda_h$. When the contract issues (does not issue) payments, $\Delta_{jk} > 0$ ($\Delta_{jk} < 0$). Under “perfect” insurance ($\phi_{\ell n}, \phi_{hp} = 0$), Q will be strictly positive as long as the contract's price does not significantly exceed the actuarially fair premium.² This expected utility-based measure provides a well-defined answer to evaluate when “false” payouts are so severe that a given insurance contract makes a farmer worse off than without and therefore is not worth buying (or selling), as well as it provides a flexible tool for comparing alternative insurance indices. For example, with a reliable measure of insurance quality, Q decreases as the following increase:

- The probability of a false negative;

¹The economics literature also refers to this λ as the shadow value of money. The rate at which the shadow value of money increases as income falls reflects the notion of risk aversion.

²The actuarially fair premium equals the expected indemnity payments $(\phi_{\ell p} + \phi_{hp})I$.

- The desperation of the farmer when a false negative occurs;
- The insurance premium, i.e., the price a farmer pays for insurance.

These principles also hold in more realistic cases with a continuum of possible yield outcomes and more complex insurance contracts.

S.2 The relationship between yields, income, utility, and risk-adjusted income

The utility measure discussed above can help us account for the outsized value of losing a dollar when incomes are low and people are risk averse. To convert incomes to utility, our case study (“Illustrating index insurance quality evaluation”) uses a Constant Relative Risk Aversion (CRRA) utility function, where y represents income, the Greek letter rho (ρ) indicates the coefficient of relative risk aversion: $U(y) = \frac{1}{(1-\rho)}y^{(1-\rho)}$. The below graphics show the relationship between a given dollar and its corresponding utility across a range of reasonable risk aversion values. In each case except for $\rho = 0$ (risk neutrality), the utility function is concave. This means that each additional dollar delivers a correspondingly lower additional utility value. This feature is known as diminishing marginal utility and is a feature of risk aversion.

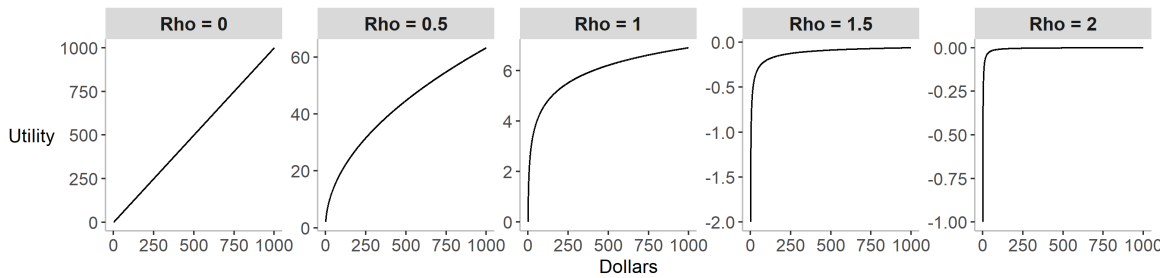


Figure S1. Comparing the Utility Equivalent of Different Dollar Values as Risk Aversion Coefficients (ρ) vary

The utility numbers on the y-axis for each graph are “ordinal, not cardinal.” In other words, it’s the relative magnitude of the difference between utility values that matters, not the particular value. Since utility values are difficult to interpret on their own, we can also convert them into an easier-to-understand measure called a “certainty equivalent,” or in the case study, the ‘risk adjusted value.’ This measure captures the idea that risk-averse people are willing to pay some amount to avoid the chance of experiencing bad, or bad to them, outcomes. As an example, imagine being offered the choice between two options (1) A gamble with equal chances of receiving either \$0 or \$100 dollars; (2) Receiving \$50 for certain. Either option nets an average (expected) amount of \$50, and a risk neutral person would be ambivalent between these two options. Risk averse people, however, would not view these options as equal. Risk averse people would be willing to receive even less than \$50 for certain in order to achieve the equivalent utility to the gamble. The amount one is willing to receive for certain that equals the utility of the gamble to them is what we call a certainty equivalent. The difference between the average of the gamble and the certainty equivalent therefore indicates how much one would be willing to pay to remove risk. In more general terms, that difference reflects how much one would be willing to give up in order to have a certain outcome over the average outcome from a gamble. The certainty equivalent in general is calculated as the inverse of the utility function multiplied by the expected (average) utility: $CE = u^{-1}E[U(y)]$. For our CRRA case, we can express that as follows:

$$\begin{cases} e^{E[U(y)]}, & \text{if } \rho = 1 \\ ((1 - \rho) \times E[U(y)])^{\frac{1}{1-\rho}}, & \text{otherwise} \end{cases}$$

Let’s now consider our case study. We see that production is variable. What is the guaranteed amount of money that one would view as equally desirable as their risky production? Step-by-step, we first converted incomes to utilities using the equations above, then translated the utilities into certainty equivalents with and without insurance. We used a risk aversion coefficient (ρ) of 1.5 – which falls within the common range for risk-averse farming communities – and we then evaluated the quality of insurance by comparing the certainty equivalents with and without insurance across our key sample indices. We assume that all income evaluated in our sample comes from agriculture, and we assume a price per ton of XX.

S.3 Estimating the Cost of Crop Cuts for an Index Insurance Contract

Throughout the main text we mention that field based yield estimation via crop cuts tend to be costly, which has given rise to interest in the alternative, remotely sensed innovations we review. How costly are we talking about, and where do the estimates come from that we use in the case study? Holding aside the procedural innovations we discuss in the main text, the total cost of each crop-cut based yield estimate will vary largely as a function of labor (wages to conduct the crop cuts), transportation (e.g., accommodations, fuel and vehicle rental/usage costs) and the equipment used to conduct the yield estimate (e.g., scales, harvest bags, tape measures, and data recording devices such as tablets). From there, to evaluate average production per zone, one would need to conduct a sufficient number of individual crop cuts so that the estimate would have a tolerable margin of error per zone.

To generate the US \$2-\$5 cost figure for using crop cuts that we discuss in the case study, we draw upon the experience of one of the co-authors in estimating yields and insurance prices for a index insurance contract for cotton producers in the Pisco Valley of Peru. Given the yield variation observed across farms in that region in any given year, they calculated needing 600 production measures to obtain a sufficiently precise (+/- 3%) estimate of average yield in the area. If we assume a price of \$40 per crop cut – which falls within the \$25-\$50 range reported by Hernandez *et al.* [1] for their work Nigeria and Kenya – then the yield estimation exercise for this area would cost \$24,000 overall. If all 12,000 hectares of cotton in the Pisco Valley area were insured, the crop cuts would thus add \sim \$2.00 per hectare to the price of insurance. If half were insured, then the price would rise to \sim \$4.00 to the price of insurance, etc.

These results depend on the number of insurance zones as well as how much yields vary within the insurance zone, and the degree of variation in this example case may well differ from the variation observed by maize farmers in Kenya used in this study. Nonetheless, one can see that with some reasonable product uptake, the cost of crop cuts could add somewhere between \$2-\$5 to the cost of the insurance per-hectare in that case as a benchmark.³ Although these numbers may overall seem small, even small price changes can affect insurance uptake², and many previous programs have indicated concern about the costliness of field-based area yield approaches (see Ceballos *et al.* [3], for example). Furthermore, although in this paper we encourage researchers to focus on the quality of index insurance rather than on uptake as the key objective of interest, uptake is nevertheless required in order to realize the potential benefits of even contracts deemed to be of high quality.

References

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2. Sibiko, K. W., Veettil, P. C., & Qaim, M. Small farmers’ preferences for weather index insurance: insights from Kenya. *Agriculture & Food Security* **7**, 53 (2018).
3. Ceballos, F., Kramer, B., Mishra, A., Robles, M., & Toor, M. S. *Picture-based crop insurance: using farmers’ smartphone pictures to reduce basis risk and costs of loss verification* Formative evaluation report. (Accessed on 10/10/2020) (July 2020).

³The actuarially fair price for this insurance was about \$35 for a contract with an 85% strike point, i.e., when yields fell below 85% of their historical average.