DESIGNING WEATHER INSURANCE CONTRACTS FOR FARMERS

In Malawi, Tanzania and Kenya

Final report to the Commodity Risk Management Group, ARD, World Bank

June 2007



Prepared by: Daniel Osgood, Megan McLaurin, Miguel Carriquiry, Ashok Mishra, Francesco Fiondella, James Hansen, Nicole Peterson and Neil Ward

International Research Institute for Climate and Society Earth Institute, Columbia University

Disclaimer

Final responsibility for the views expressed in this report lies with the authors. The views are not necessarily those of the World Bank, NSF, or NOAA.

Contact:

Daniel Edward Osgood Associate Research Scientist in Economic Modeling and Climate International Research Institute for Climate and Society The Earth Institute at Columbia University deo@iri.columbia.edu http://iri.columbia.edu Phone: (845) 680-4461 Fax: (845) 680-4865

Correct citation

Osgood, D.E, McLaurin, M. Carriquiry, M., Mishra, A., Fiondella, F., Hansen, J., Peterson, N., and Ward, N. (2007). Designing Weather Insurance Contracts for Farmers in Malawi, Tanzania, and Kenya, Final Report to the Commodity Risk Management Group, ARD, World Bank. International Research Institute for Climate and Society (IRI), Columbia University, New York, USA.

This report was funded by the Commodity Risk Management Group, ARD, World Bank and the US National Oceanic and Atmospheric Administration (NOAA), which provided its support under cooperative agreement NA050AR431104. Some products were provided to the project at no cost by the Center for Environmental Research and Decisionmaking, established under the National Science Foundation Program Decision Making Under Uncertainty (DMUU).

Additional partners who have provided substantial contributions to this project include (in alphabetical order) the Chitedze Agricultural Research Station, CIC, ECLOF, Equity, FSD Kenya, ICRISAT, Insurance Association of Malawi, Kenya Meteorological Service, Malawi Meteorological Service, Malawi Rural Finance Company Limited (MRFC), National Smallholder Farmers' Association of Malawi (NASFAM), Opportunity International Bank of Malawi (OIBM), Pride Tanzania, Tanzania Meteorological Service, Technoserve, World Bank

IRI Technical Report 07-02

DESIGNING WEATHER INSURANCE CONTRACTS FOR FARMERS IN MALAWI, TANZANIA AND KENYA

Final report to the Commodity Risk Management Group, ARD, World Bank

Daniel Osgood, Megan McLaurin, Miguel Carriquiry, Ashok Mishra, Francesco Fiondella, James Hansen, Nicole Peterson and Neil Ward

International Research Institute for Climate and Society, Earth Institute, Columbia University

TABLE OF CONTENTS

EXECUTIVE SUMMARY
OVERVIEW
Contract Design
Basic structure of contract
Design process
REFERENCE SECTIONS
1. Design Illustration23
2. Overview of changes from original design
3. Changes in phase payout function
4. Discussion of crop stress methodology28
5. Loss proxy
6. Optimization
7. Index Insurance Complexity
8. Portfolio pricing
9. Forecast and insurance40
10. Description of contract communication tool46
CONCLUSION

APPENDIX I. Description of all contracts50	
Malawi contracts	
Tanzania56	
Kenya	
APPENDIX II. Pseudo-Pricing alternatives pursued	
APPENDIX III. Varying yield stress in WRSI based loss calculations64	
APPENDIX IV. Potential Evapotranspiration	
APPENDIX V. DSSAT model background	
APPENDIX VI. Data requirements	
APPENDIX VII. Cooperative design questionnaire	
APPENDIX VIII. Initial Explorations of Failed Sowing72	
APPENDIX IX. Additional Simulations	
APPENDIX X. Contract communication tool	
BIBLIOGRAPHY	

ł

(

(

EXECUTIVE SUMMARY

his report presents project products to the Commodity Risk Management Group of the World Bank for the development and evaluation of index insurance contracts for smallholder farmers in Malawi, Tanzania, and Kenya. The development of some products we are providing was supported at no cost by the NSF-funded Center for Research on Environmental Decisions.

Index insurance is a relatively new weather risk management tool. While traditional insurance insures against crop failure, index insurance insures for a specific event or risk, such as rainfall deficits. The index insurance can be more cost effective since there is no need for in-field assessment of damage because payouts are triggered by weather data directly. Index insurance addresses two problems associated with traditional crop insurance: moral hazard (incentives for a farmer to let a crop die in order to get an insurance payout) and adverse selection (in which insurance is priced based on the risks of the entire population but only the most vulnerable farmers purchase insurance).

However, index insurance only provides partial protection and is therefore only one part of a complete risk management package. It is critical that the client have a comprehensive understanding of exactly what risks are covered (and what risks are not covered) by the index product so that clients can effectively use the insurance as a part of their risk management system. Products must be transparent and completely understandable to the client or they will not be able to play their proper role.

We designed and evaluated contracts for Malawi, Kenya and Tanzania. Because some contracts existed for Malawi prior to this project, and since the insurance is in its second year of implementation in Malawi, the Malawi initial contracts and implementation are used as a starting point. Following the project specification, we have developed in depth analysis, such as process based crop simulations and quantitative analysis of historical data, for the Malawi case study. These additional analyses are unique to the Malawi case.

In general, the contract development and evaluation process has led to a set of contracts that appear to perform extremely well. So much so, that demand in many places has overwhelmed administrative capacity to serve clients. As this is an unsubsidized product that is purchased by clients, some indication of its value can be seen in its market demand. In interviews, farmers have stated that their primary strategy for adaptation to climate change is enrollment in the insurance program. Much of this success is due to the outstanding input and support from project partners, including strong data and analysis support from the Malawi, Kenya, and Tanzania Meteorological services. Because of their wide range of competencies, it is likely that these Meteorological services could play a much expanded role in project scale up.

There are several issues that we addressed in evaluating and improving the initial Malawi 2005 pilot contract design process for updated contracts in Malawi Kenya and Tanzania. First, the initial Malawi contracts had particular features in the formulas that we modified in order to increase robustness, performance, flexibility, and transparency. Second, we extended the design process to include more statistical analysis so that contracts addressed climate characteristics as well as agronomic features of crops. We evaluated and improved the crop water stress calculation techniques to more effectively represent drought related risk in the contract. We developed a systematic design methodology that could utilize the strengths of each source of imperfect information. Finally, we provided formal mechanisms to incorporate financial constraints in the contracts.

There are several important issues that have yet to be addressed in the design of future contracts, in order to ensure that the product evolves into a fully sustainable and scalable product. It is important to build capacity for local design and adaptation of contracts as existing needs change and new needs are identified. It is critical that the pace of product upscaling does not exceed the pace of capacity development and project improvement. In addition, the design process must be updated in order to allow for information in seasonal precipitation forecasts to be utilized in the insurance strategy. Crop breeding programs can be integrated into this process. Contracts could be developed further to more elegantly address failed sowing issues and sporadic starts to the rainy season. Index contracts and reinsurance must be designed acknowledging regional and global climate features, since large scale climate processes can lead to negatively correlated seasonal rainfall between regions.

Work should be done to more accurately and transparently characterize the distributions underlying historical precipitation that lead to losses and payouts beyond historical burn analysis we used for improved characterization of risk. Techniques must be developed to interpolate information between stations and to use satellite based products. These, and related techniques should be advanced to enable a quality product to be established when a new station is installed, to detect data tampering, to reduce basis risk, and perhaps enable the availability of index products where met stations are not available. Indexes should be explored to cover additional risks, such as excess rainfall. It is worthwhile to utilize economic contract theory to develop incentives that discourage tampering and encourage accurate farm reporting. Contracts could be designed to reveal the value of insurance through market transactions. It is important to develop communication tools for cooperative design, education of contract issues, and exercises to test for farmer understanding of products.

OVERVIEW

In this report, we describe our project products to World Bank's Commodity Risk Management Group (CMRG) in the development and evaluation of index insurance contracts for smallholder farmers in Malawi, Tanzania, and Kenya. The development of some products we are providing was supported at no cost by the NSF-funded Center for Research on Environmental Decisions.

Index-insurance is one type of weather risk management that has recently developed as a potential tool to reduce weather risk in agriculture. While traditional insurance insures against crop failure (actual loss), index insurance insures for a specific event or risk, such as rainfall deficits (Skees 1999). Thus, the index insurance removes one or more production risks, but does not account for the loss itself. This method addresses two problems associated with traditional crop insurance: moral hazard (where farmers have incentive to let their crops fail in order to receive a payout) and adverse selection (where those farmers less skilled at farming purchase the insurance, resulting in higher premium levels and more frequent payouts). Since the index insurance only covers a specific risk, it only provides partial protection and is therefore only one part of a complete risk management package. The index insurance also becomes a more affordable option, in that there is no need for in-field assessment of damage, as damage is able to be tracked by weather data directly (in the case of rainfall, a rain gauge would be the device used).

The Malawi experience provides an example of the potential for using index insurance in developing countries to assist emerging markets and increase productivity of small holder farmers, with a bundled index insurance, loan, and input package in its second year of implementation. Our project supports this implementation. Partners include the National Smallholder Farmers' Association of Malawi (NASFAM), in conjunction with the Opportunity International Bank of Malawi (OIBM), the Malawi Rural Finance Company Limited (MRFC), the Insurance Association of Malawi, and the Malawi Meteorological Service, with support from the World Bank CRMG and IRI. ICRISAT and the Chitedze Agricultural Research Station provided important and influential input in the design process.

Following the project Terms of Reference, we designed and evaluated contracts for Malawi, Kenya and Tanzania. Because some contracts existed for Malawi prior to this project, and since the insurance is in its second year of implementation in Malawi, the Malawi initial contracts and implementation are used as a starting point for other contracts and countries. Following the project specification, we have de-

veloped in depth analysis, such as process based crop simulations and quantitative analysis of historical data, for the Malawi case study. These additional analyses are unique to the Malawi case.

Small holder farmers in Malawi have reported that they would be able to increase their yields and income if they were able to buy the higher quality inputs (hybrid seeds and fertilizer) necessary for increased production. Illustrating the potential benefits for maize, estimates of national maize yield for Malawi for the 2006/2007 growing season show local varieties of maize yielding about 50% less maize per hectare than the hybrid maize (Malawi Department of Meteorological Services 2007). In the past, many small holder farmers have been unable to purchase these inputs, such as the hybrid maize seed, fertilizer, and hybrid groundnuts, because they lack the necessary capital.

Microfinance institutions in Malawi have been uncomfortable providing loans to these farmers because they face high risk of crop failure, making it questionable if the farmer would be capable of paying back the loan. Rainfall deficits are a dominant risk faced by farmers in Malawi. Index insurance has been used as a means of removing the risk of rainfall deficits, supplying the microfinance institution with the confidence necessary to give the farmer the loan and the farmer with the capital necessary to purchase higher quality inputs, and in turn increase productivity and income.

The insurance is a part of a finance/production bundle. Illustrating with the Malawi groundnut example, the package is designed for 1 acre of production. To be eligible, a farmer must be within 20km of one of the met stations in the program. A typical groundnut package consists of a loan (~4500 Malawi Kwacha or ~\$35) that covers the groundnut seed cost (~\$25, ICRISAT bred), the insurance premium (~\$2), and tax (~\$0.50). Upon signing the paperwork, the farmer receives a bag of groundnut seed sufficient for 1 acre of production and an insurance certificate for a policy with a maximum payout of the loan size plus interest (~\$7). The prices vary, of course, by weather station and crop. Farmers are organized into joint liability groups of approximately 10-20 members. The farmers plant the groundnut



seed, and at the end of the season provide their yields to the farm association, which markets the yields. Proceeds and insurance payouts are used to pay off the loan, with profits returned to the farmer.

In Kenya and Tanzania, similar products are being developed. In Tanzania, Pride Tanzania, the Tanzania Meteorological Service, and Technoserve are some of the partners. In Kenya, some of the partners are the Kenya Meteorological Service, FSD Kenya, ECLOF, Equity, CIC. The parameters for all contracts are presented in Appendix 1.

In general, the contract development and evaluation process has led to a set of contracts that appear to perform extremely well—so much so, that demand in many places has overwhelmed administrative capacity to serve clients. In interviews, farmers have stated that their primary strategy for adaptation to climate change is enrollment in the insurance program.

As the loan/insurance are unsubsidized products purchased by clients, some indication of their value can be seen in its market transactions. Since thousands of loan/insurance have been voluntarily purchased by farmers in Malawi, the price that they have paid provides a minimum bound on the value they place on the product. Much of this success is due to the outstanding input and support from project partners, including strong data and analysis support from the Malawi, Kenya, and Tanzania Meteorological services. Because of their wide range of competencies, it is likely that these Meteorological services could play a much expanded role in project scale up. It is important to ensure that mechanisms exist to provide resources for Meteorological agencies for the necessary data collection, cleaning, reporting, and analyses.

For the future, it is critical that the pace of product upscaling does not exceed the pace of capacity development and project improvement. If pilot contracts and stakeholders cannot evolve at a pace exceeding scale up, pilot contracts may be extended beyond their limits. If financial stakeholders do not have the sufficient understanding and capability to update the products, they may not understand the important limitations of index products, and farmers may not understand what risks the contracts do not provide protection for. This is particularly important for index products, since both the provider and client must fully understand that the product does not protect against all losses, and must understand how to build risk protection against the risks the contract does not address.

There are several issues that we addressed in evaluating and improving the initial Malawi 2005 pilot contract design process for updated contracts in Malawi, Kenya and Tanzania. First, the initial Malawi contracts had particular features in the formulas that were modified in order to increase robustness, performance, flexibility, and transparency. Second, given the deterministic agronomic modeling focus in the initial Malawi contract design, it was important to extend the design process to include more statistical analysis to arrive at contracts tuned both to agronomic features of crops as well as climate characteristics. We evaluated and improved the crop water stress calculation techniques to more effectively represent drought related risk in the contract. Since agronomic models have a finite level of skill in reflecting actual losses, and since each source of information about losses has limits in terms of reliability and accuracy, we developed a systematic design methodology that could utilize the strengths of each source of imperfect information. Finally, we provided formal mechanisms to incorporate financial constraints in the contracts. See Contract Design and Reference Section 2.

There are several important issues that have yet to be addressed in the design of future contracts, in order to ensure that the product evolves into a fully sustainable and scalable product. Perhaps the most important is to build capacity for local design and adaptation of contracts as existing needs change and new needs are identified. In addition, the design process must be updated in order to allow for information in seasonal precipitation forecasts to be utilized in the insurance strategy. Crop breeding programs can be integrated into this process, leading to varieties that are adapted to play the best role possible in the bundled insurance/credit/forecast system. Contracts could be developed further to more elegantly address failed sowing issues and sporadic starts to the rainy season. Index contracts and reinsurance must be designed acknowledging regional and global climate features, since large scale climate processes typically lead to negatively correlated seasonal rainfall between regions. Work should be done to more accurately and transparently characterize the distributions underlying historical precipitation that lead to losses and payouts to bring design and pseudo-pricing beyond historical burn analysis to utilize Monte Carlo based simulation for improved characterization of risk. Techniques should be developed to interpolate information between stations and to use satellite based products.

These, and related techniques should be advanced to enable a quality product to be established when a new station is installed. These techniques would be critical for other issues, such as detecting data tampering, reducing basis risk, and perhaps enabling the availability of index products where met stations are not available. It is worthwhile to utilize economic contract theory to develop incentives that discourage tampering and encourage accurate farm reporting. Contracts could be designed to reveal the value of insurance through market transactions. It is important to develop communication tools for cooperative design, education of contract issues, and exercises to test for farmer understanding of products. Indexes should be explored to cover additional risks, such as excess rainfall. See *Design Issues that Must be Addressed in the Future* in the next section.

This report is one of the deliverables for the project. Another deliverable for this project is the R programming code that we developed to support our contract design and analysis. It is not finalized robust code. It is not designed to be a tool, and it contains outdated code fragments not used in our final analyses. It is presented for the sake of transparency in analysis to serve as additional documentation on the methods and data we used. An additional deliverable for the project is the Contract Communication Spreadsheet that illustrates each index contract. This was produced with the support of the NSF funded Center for Research on Environmental Decisions at no cost to the project.

CONTRACT DESIGN

The design process leading up to the original Malawi contracts is used as a starting point for the updated design process. Most of the basic features of the original contracts were retained and built upon. We proceed with an overview of the basic contract structure and design process. This overview is followed by sections that elaborate on specific issues.

Basic structure of contract

All contracts were based on dekadal (10 day)¹ rainfall summaries, and dekadal totals were limited to maximum levels (caps). Any rainfall above the cap within a dekad is not considered in the payment formulas. A "sowing window" is set for each contract with a start dekad and an end dekad. The con-

tract calendar begins in the first dekad of the sowing window for which rainfall exceeds a threshold amount, the "sowing trigger." If the trigger is not exceeded during the window, a failed sowing condition is signaled, a failed sowing payment is paid, and the contract is terminated. If the sowing trigger is reached, the contract calendar begins with the dekad in which the trigger was reached. The contract calendar is broken up in to a number of phases of several dekads each (three phases were used in most cases). Payouts are calculated using simple piecewise linear formulas of the sum of capped dekadal rainfall occurring over the phase.



The payout function for each phase has three parameters, a trigger, an exit, and a maximum payout. If the capped rainfall total during a particular

1 The first dekad of each month is defined from the 1st to the 10th of the month; the second from the 11th to the 20th of the month; the third, from the 21st to the end of the month, can have from 8 to 11 days.

phase is more than the trigger, no payout occurs for that phase. If the rainfall total is less than the exit, the maximum payout is rewarded. If the rainfall total is between the trigger and exit, the payout is linearly interpolated between the zero level payout at the trigger and the maximum payout at the exit using the simple linear formula below (with an example illustrated in Figure 3.2).

For a description of how this formula was changed from the initial contracts, see Reference Section 3. The total payout is the sum of the payouts for each phase and limited to the maximum payout size. Contract timing and parameters are determined using agronomic models and rainfall data in a numerical optimization that minimizes the variance in income that a farmer would face subject to a maximum premium constraint, as described in the following sections.

Design process

The design process begins with gathering initial information of crop and climate characteristics (see data requirements Appendix 6.). As with any business, in farming, many of the details of cost, productivity, and risk exposure are proprietary or personal and may be carefully guarded if the producer is not naive. If fully revealed, they could put the producer in a disadvantageous position with competitors, banks, or insurance companies in negotiations. This 'private information' might be hypothetically used by a bank, insurance company, or input provider to calculate how high rates, fees and prices might be raised above cost before a farmer would step away from the negotiating table. Therefore, the design process must be compatible with a business negotiation environment in which players may lose if they show all their cards. We must have design strategies that can lead to contracts in a setting in which players can reveal as much personal private information as they feel comfortable with.

In the original contract design process, insurance coefficients were directly calculated using crop modeling parameters. In the improved design process, this is merely the starting point. Since contract parameters from the more complete design process must now systematically reflect a combination of agronomic, climatic, and financial features they are not directly interpretable in terms of Water Requirement Satisfaction Index (WRSI) calculations.

Sowing Conditions

The WRSI based model is used as a mechanism to represent expert information in a mathematical form. See http://www.fao.org/ag/AGL/aglw/cropwater/cwinform.stm and CRMG 2005. Reference Section 4 and Appendix 5 of this report explain the WRSI model in greater detail as well as our evaluation of alternate WRSI models. In the WRSI model, the beginning of the growing season, length of the season, timing of crop growth, the timing of various developmental stages, and the timing of vulnerability to water stress must be explicitly assumed. If the timing assumptions are incorrect, the simulation will predict water stress in inappropriate parts of the season. Therefore the WRSI based model is only as useful as the information used to calibrate its parameters, and its timing assumptions must be verified with farmers. When inconsistencies are found, or new information is available, it is important to update the parameters to reflect the fundamental stresses to the crop. The initial sowing condition (in mm of

precipitation/dekad) is selected based on FEWSNET and FAO criteria (following CRMG 2005) and adjusted to be as consistent as possible with common planting schedules observed in the field. An initial selection of the dekadal cap is also selected using the WRSI based calculations (again following CRMG 2005).

Selecting Phases

The information on crop growth phases from the WRSI model calibration are used in the initial selec-



tion of dekads for the sowing window and contract phases. Strategic trade-offs must be considered in order to determine phase timing. Phases may be timed to directly coincide with all growth stages. The phases may represent grouped growth stages to yield a more simplified contract. Alternately, growth stages may be divided in order to more accurately target growth stress.

The selection of phase length involves a trade-off. Phases that are too short may lead to a contract that is out of sync with the actual production process, one that misses a critical dry spell because the contract calendar does not exactly match the crop phonological stage. If additional dekads are included in a contract phase before and after

anticipated vulnerability, then it is more likely that the vulnerable growth stage will fall in the anticipated contract phase when the contract is implemented. On the other hand, inclusion of additional dekads to a phase means that the phase total will be less sensitive to dry dekads within the phase, potentially averaging out a significant dry spell. Growth stages for which there is little or no stress might be eliminated from the contract (particularly if these are the final drying stages of the crop).

Determining Payout Frequencies and Working with Price Constraints

In designing the insurance contracts, there are financial constraints. A contract must payout at a rate that is approximately equal to the demanded frequency. In addition, the contract cannot be too expensive. Ranges for payout frequency and price constraints must be determined through interviews with financial stakeholders and farmers. In order to cover losses for a given insurance price, there is a balance between a higher frequency of smaller-sized, partial payouts, and a lower frequency of large payouts. A larger deductible (higher triggers) leads to larger, less frequent payouts. Raising the exits increases the size of payouts without changing the times when payouts would occur. See Reference Section 1.

Incorporating Climate Features

The WRSI model parameters should not be taken as a definitive predictor of crop behavior. They are merely a starting point because much of the protection that an insurance contract provides is climate driven, not crop vulnerability driven. A crop that is adapted for the local climate will have low water

stress vulnerability during the parts of the season that are typically dry. Drought vulnerability is a balance between the particular strengths of the crop and the water stress challenges presented by the local climate and a drought protection contract must explicitly address this balance in its design. It is therefore important to design contracts that balance agronomic parameters with climate features. This balance is evident even in the way that water stress models are applied to forecast yields. The FAO group that initially developed the WRSI model does not directly apply it when forecasting yields. Instead they recommend a regression based prediction using variables that are inputs to the water stress model.

Optimization

In order to arrive at a contract, a numerical contract optimization is performed on a WRSI based crop loss measure associated with the rainfall data (see Reference Section 6). We have developed code for the R statistical system to perform much of our analysis. The objective function of this optimization is to minimize the variance in losses less insurance payments subject to the insurance price constraint. Because the final price of the contract is determined through negotiations between stakeholders, an unofficial "pseudo price" is used following standard and transparent risk pricing methods (see Appendix 2). The triggers of the contracts are the decision variables for the optimizer. In other words, the optimizer minimizes the variance of losses (see Reference Section 5 for details on the loss proxy) that a hypothetical farmer would face if that farmer had purchased the insurance by adjusting the triggers while maintaining a maximum insurance pseudo price. In order to ensure the price must not go above the constraint, when the optimizer raises the level of one trigger, it lowers the levels of the others. Therefore the task of the optimizer is to determine the relative levels of the triggers.

Because this is a complex optimization problem, the optimization engine cannot be guaranteed to find a global optimum, but instead will recover a local optimum that is best adapted from the initial guess



provided. In essence, the engine cannot determine the best strategy for a contract, but can tune that strategy to be most efficient. In addition, there are design trade-offs that the optimizer is ill suited to make, particularly given the high level of private information about risk exposure and risk preferences in the index insurance design problem. Since it is preferable to have many of these trade-offs explicitly negotiated between stakeholders as opposed to decided by a computer, the optimization algorithm is purposefully focused to address cost effectiveness trade-offs. Therefore it is important to apply the optimizer to a variety of alternate contract strategies. In order to uncover potentially effective contracts, it is worthwhile to perform an optimization run with each one of the triggers dramatically larger than the others (see Reference Section 1).

The trade-off between payout frequency and payout size for contracts resulting from the optimization process can be adjusted by modifying the exits. Lowering triggers helps to reduce the payout frequency for a given price, while raising them increases the frequency. When additional contract strategies are necessary to meet all of the constraints a contract faces, it may be useful to run the optimizer with an artificially high or low price constraint to result in a contract that has the desired features, and then to use the resulting contract as the initial guess for a contract with appropriate price constraints.

There are a variety of loss indicators that may have some relevance, so it is worthwhile to assess the draft contracts against these indicators as well. For the crops that we have designed drought stress contracts for, we have determined that losses derived from a WRSI index using daily precipitation and with seasonally varying water stress weights is the most effective benchmark for applying the optimization engine (see Reference Section 4).

It is important to note that WRSI simulations are likely not to be the most accurate representation of total yields and may under-represent the risk faced by the farmer. However, they are a relatively robust, practical, and transparent tool to represent the dynamics of crop water stress in contract design, so long as they are not interpreted as representing more information than they embody. For other applications, where forecasts of absolute yield levels are required (such as national yield forecast systems), related, but alternately specified water stress algorithms that combine water stress indicators with statistical yield analysis are preferable (Chavula 2006).

Additional Information Sources for Contract Design

Historical Yield Data

Historical district level yield data is one information source that may be available to assist in contract design. In addition, it is likely to represent a different set of farmers using a different set of practices, inputs, and conditions than those being insured. As opposed to simulation output, all sources of yield variation are represented in the time series, instead of only drought stress related losses. This means that a long time series is necessary in order to characterize the drought related yield losses in historical data. However, this data is typically of limited quality, consistency and only available for brief periods of time. Since it is the average of yields over a district, much of the variance in individual production is lost, masking the potential severity of individual losses. However, it provides an independent, non-model based source of information for assessment of the contract. Therefore, it is typically not the best choice to optimize a contract using this information when a better loss indicator is available. Though, it is important to gauge the performance of a proposed contract against historical yields to insure unless

the time series is so short that the contract being considered does not have any payouts during that period. If the contract were to perform extremely badly against events represented in the historical data set, stakeholders should be comfortable with the reasons for this lack of performance before accepting the contract.

Process Based Crop Models

For Malawi, we have studied the effectiveness of utilizing output from process based crop models that are more sophisticated than WRSI based models. We recommend that these models not be used as the benchmark for optimization, as they tend to be highly sensitive to assumptions for parameters. They are more likely to represent the losses accrued by an individual farmer with very particular characteristics than the entire community to be covered by the contract. Therefore, their utility is primarily in developing a more detailed understanding of why crops might be stressed in a particular year, improving the WRSI model assumptions, and checking the robustness of a draft contract (see Reference Section 4 and Appendix 5).

Farmer Interviews and Feedback

Contracts should be gauged against farmer recollections of difficult years, particularly if the farmers can recall the growing phase during which a crop faced difficulties in a particular year. As with the historical yields, this information is likely to be noisy. However, it also provides an important gauge that could distinguish a robustly performing contract from one that is inappropriately designed. This interaction is important for several additional reasons. Since the timing of stress in the WRSI model is directly assumed, it is worthwhile to verify with farmers that the sowing times and periods during the season in which the crop faces the most stress are those assumed in the WRSI model, and represented in the contract phase timing choices. This interaction provides farmers with the opportunity to reveal more private information if they feel it is worthwhile to do so for an improved design. Finally, it helps ensure that farmers understand what the product is, what types of events it will cover, and what types of events that it will not cover so that they can make educated insurance purchases and farm management choices. In this process, we have cooperated in the development of a tool to aid in the communication of contracts with farmers and test if farmers are able to understand the contract (see Reference Section 10 and Appendix 10).

Contract Evaluation

A variety of performance indicators are produced by the software, and it is worthwhile to assess the draft contract performance with respect to each of the indicators.

Payout Timing

The timing of payouts may be important. In a year with severe losses, a farmer may be more concerned with the existence of a payout at all than how exactly it corresponds to revenue losses. In discussions with farmers about past years it is much more likely that they will recall the year of a historical loss than the exact size of the loss. Therefore the timing of payouts may be the only diagnostic available to gauge contracts against these types of data sources. The timing of losses and payouts is presented in the output of the software in a table ranking the losses from largest to smallest and indicating if there was a payout in each year. In addition, the software summarizes the number of payouts in the worst half, third, and quarter of the losses.

Correlation between Payouts and Losses

It should be noted that the correlation between the payouts and losses, although a useful diagnostic for distinguishing a well performing contract from one that performs badly, is not the appropriate objective function for the optimization engine. Achieving the highest level of correlation between payouts and losses is not the primary design objective. Because it is scale neutral, a contract that provides very little protection, but provides the protection at effective times, can have a correlation that is much higher than a contract that provides more protection. In addition, it is important to note, that in our analysis, the correlation between model-based losses and payouts is artificially inflated when there are failed sowing conditions because our assumptions for a sowing failure are identical in the contract and WRSI based loss model. This effect is intensified because failed sowing conditions are typically high payout events modeled as a complete loss. Nevertheless, the standardized correlation provides a useful parameter for contract assessment, and all of the contracts presented here have high correlations with payments.

Manual Adjustment to meet Stakeholder Needs

Following the automated optimization process, it is typically important to adjust contract parameters slightly to better represent objectives not directly modeled in the optimization. In addition, the use of triggers and exits that are specified to a high level of precision may incorrectly suggest that the data sources driving the analysis are more precise than they actually are. Since it is important that farmers gauge the contract against their own experience, it may be worthwhile to adjust contract parameters to round numbers to help ensure that the farmer understands the appropriate level of precision that the contracts reflect. Since contracts are typically bundled with a loan, the central purpose of the contract is to protect the loan. For this reason, the goals in contract design must be different than in instances where the contract is simply addressing a farmer's risk. The bundling of the contract with the loan means that more stakeholders are involved, whose input must be taken into account in contract design.

Following this cross verification process, the contract design is repeated, updating the WRSI and contract phase parameters to most effectively represent the new information gained in the feedback and evaluation process until contracts are developed that all stakeholders are comfortable with in terms of their properties, performance, and complexity (see Reference Section 7).

Design issues that must be addressed in the future

Before presenting the design process we emphasize that these contracts represent an early step in a technology that must continually evolve with upscaling and changing needs. There are several important issues that have yet to be addressed. Perhaps the most important is to build capacity for local design and adaptation of contracts as existing needs change and new needs are identified. The potential for this capacity exists in the National Met agencies, local financial institutions and farmer oriented organizations, but it cannot be harnessed unless specific technical skills are developed and supported.

Capacity Building

The need to build capacity for local design and adaptation of contracts increases in importance if the insurance is successful in allowing economic development. A product that is designed to provide a stepping stone for farmers into the cash economy must adapt once these farmers (who previously did

18

not have access to loans, savings, or cash) make the transition and begin to establish credit ratings and accumulate money in savings accounts. With each step of the development process, the insurance tools must grow with the clientele.

It is critical that the pace of product upscaling does not exceed the pace of capacity development and project improvement. If pilot contracts and stakeholders cannot evolve at a pace exceeding scale up, pilot contracts may be extended beyond their limits. If financial stakeholders do not have the sufficient understanding and capability to update the products, they may not understand the important limitations of index products, and farmers may not understand what risks the contracts do not provide protection for. This is particularly important for index products, since both the provider and client must fully understand that the product does not protect against all losses, and must understand how to build risk protection against things the contract does not address (see Reference Section 7).

The analytical expertise to link a contract formula to crop losses or otherwise address basis risk may not exist in a financial institution established for the provision of traditional insurance. The importance of properly designed contracts is not always central to the provider with experience in traditional insurance because the provider is used to relying on adjusters to directly observe loss instead of performing research to model the loss. In addition, since the provider does not directly face the consequences of basis risk, substantial capacity building may be necessary to ensure that the problem is addressed in scale-up. Even with a well designed contract, it is possible to increase the risk that a farmer faces by ensuring maximum liabilities that are too large relative to the risks faced, which could pose a danger if a product is mainstreamed without appropriate stakeholder capacity.

Seasonal Precipitation Forecasts and Spatial Climate Features

In the future, the design process must be updated in order to allow for information in seasonal precipitation forecasts to be utilized in the insurance strategy. For full scale up, contracts must be robust to inter-temporal adverse selection. That is, a client should not be able to use the forecast to undermine the financial stability of the insurance through a strategy such as purchasing insurance only in years with drought forecasted. For the current pilot implementations, for which total demand is greater than the pilot size, this is not yet an issue. However, as projects are upscaled, it becomes increasingly important. In addition, a failure to integrate forecasts and insurance would result in an important opportunity being lost. It is likely that the insurance could be used in concert with the forecast to yield substantial benefits by reducing losses in bad years and allowing additional intensification in good years. These issues are discussed through the exploratory analysis presented in Reference Section 9.

Index contracts and reinsurance must be designed acknowledging regional and global climate features, since large scale climate processes typically lead to negatively correlated seasonal rainfall between regions. For example, an ENSO state that is associated with higher probabilities of drought in Southern Africa is correlated with ample rainfall in the Greater Horn of Africa. On smaller scales, year to year climate processes often lead to rainfall occurring on alternate sides of a mountain range. Even when the location of rainfall cannot be predicted, an understanding of the negative correlations between regions could be used to reduce costs. An exploratory presentation of this issue is provided in Reference Section 8.

Accurate Characterization of Probability Distributions

Work should be done to more accurately and transparently characterize the distributions underlying historical precipitation that lead to losses and payouts to bring design and pricing beyond historical burn analysis to utilize Monte Carlo based simulation for improved characterization of risk. Currently, for the sake of transparency and simplicity, pricing and design analysis is primarily based on analysis directly using historical payouts. Since this analysis approach leads to products and prices that are sensitive to the particular features of one or two historical events, they can overemphasize the importance of the specifics of these events. This improvement in the characterization of probabilities is important both in contract design and in final pricing.

The demands of index insurance design taxes current methods to model the underlying distributions, simulate rainfall, or characterize the probability weights in distributional tails. A technique must be able to accurately represent probabilities for variables such as the rainfall at each point in the season, the correlations between points in the season for a particular year, and the frequency of rare catastrophic events that may not have been exhibited in the available historical data.

It is possible that a particular technique, although sophisticated, might mischaracterize probabilities, and that this mischaracterization could be undetected due to the complexity of the technique. If results of a given technique are entirely driven by model assumptions, these assumptions may be masked by complexity of the technique, leading to misinformed decision making. Therefore it is important to evaluate and extend current techniques to ensure that contracts can be appropriately designed and priced making full and transparent use of the information available.

When only short historical data series are available, techniques must be available to appropriately quantify the uncertainty in the probabilities of events so that this uncertainty can be priced into products, and insurance can be designed to cover anticipated risks. This is particularly important when new Met stations are brought online to provide index insurance for additional regions.

When a new station is established, typically there are several alternatives to characterize the historical behavior of rainfall. These can include sub-standard station-based data, data from relatively nearby stations, and satellite based products. As scale up occurs, it is important to develop transparent and robust techniques to utilize these data sources to enable a quality product to be established when a new station is installed. These techniques would be critical for other issues, such as detecting data tampering, reducing basis risk, and perhaps enabling the availability of index products where met stations are not available. In the Malawi case, it may be worthwhile to use nearby stations to study issues of rainfall interpolation and basis risk. For example, the Lilongwe and Chitedze stations are approximately 25 km apart, so they have overlapping areas of coverage, with EPA (sub district) level historical yield data and extensive research on local groundnut drought stress.

Issues regarding contract design

The bundling of index insurance with other contracts (such as loan contracts) has not been fully addressed in economic contract theory (the theory of design of contracts). Through application of contract theory it may be possible to use the strengths of the index based contract to reduce moral hazard issues in lending, instead of simply reducing the risk to the lender. One result might be contracts that provide incentives for farmers to accurately report rainfall or yields. This analysis might also allow market based valuation of the insurance product and tests to determine if the farmers understand the product.

Evaluation Issues

In valuation, nascent bundled insurance products are more complex than evaluation of subsidized products that have existed for several years (such as scholarships), so these studies must be developed with considerable design finesse. Since the insurance product is a non-subsidized voluntary market transaction, there is baseline evidence for value of the product. The value of the bundled product is, of course equal to, or greater than the value paid for it.

Since the bundle is complex, and designing studies of its value would require understanding the role of varying basis risk, the multiple elements of the finance package, the implications of missing markets, the non-continuous nature of the package, and the constraints imposed in order to arrive at a workable package. It may be possible to design contracts that facilitate the valuation of the product in a seam-less manner. The insurance market may provide evidence of the value of complimentary sources of risk reduction, such as forecasts. The study design for such efforts will need to be carefully engineered, and may require strategic use of partially subsidized products in order to enable valuation of individual package components.

Communication Tools for Farmers and Stakeholders

Since index insurance only provides partial coverage from risk, it is important that farmers who purchase the insurance understand exactly what the insurance does, and does not cover. In addition, index insurance is typically applied because private information problems make traditional insurance (and uninsured loans) infeasible. Design of the insurance must be able to incorporate the essential input from farmers without forcing them to reveal private information that might be used against them by competitors or in negotiations. Thus those designing the insurance will typically not have the full set of information available. Instead insurance requires design input from all levels of stakeholders, including farmers, and the benefits and limitations of the products must be completely understood by the farmers. It is important to develop communication tools for cooperative design, education of contract issues, and exercises to test for farmer understanding of products.

Addressing Additional Risks

It will be important to investigate the possibility of using index insurance to address additional risks, such as those associated with excess rainfall, or more complex crops. Crop problems such as aflotoxin might be addressed by building upon aflotoxin early warning models being developed at the University of Georgia by ICRISAT for groundnuts in West Africa. Because models for these more sophisticated problems have much lower levels of accuracy as models for drought stress in annual crops, it is not possible to use model output as the foundation for contract design. Therefore, a much higher level of communication with experts, farmers, and other stakeholders will be necessary in order to design these products, so it is important to develop stakeholder capacity and cooperative design and educational tools for this purpose.

Covering Failed Sowing Events

It may be worthwhile to develop a more sophisticated coverage of failed sowing events. Because these are currently a binary condition in the contract, a single mm of rainfall could lead to a full contract payout or no payout at all. Therefore, if the rainfall is close to the critical levels, issues of measurement accuracy may become problematic. Sowing problems may occur due to a sporadic start of the rainy season as opposed to no rainfall at all. In addition, since a failed sowing event occurs early in the season, there are an array of options that a farmer might chose to avoid losses on the scale that would occur if the crop were to fail late in the season. In the current contracts, we have explored adjusting the maximum payout associated with a failed sowing event and have also used payouts in the first phase as a mechanism to provide coverage for sporadic rains early in the season. However, it is likely that it would be worthwhile to develop simple and transparent but more continuous and effective mechanisms for addressing sowing failure. A brief discussion of one strategy is mentioned in Appendix 8.

Integrating local and regional experts

As scale up occurs, further efficiencies could be identified by closer integration with local and regional experts. Groups such as ICRISAT advocated strongly that they be more involved in the package design, as they have a family of varieties that could be applied, have yield and phonological timing trials with NASFAM farmers, and have a long term breeding program that could be integrated with the long term plan of the project. Flexibility in the packaging might provide farmers with the seed (or portfolio of seeds) suited to their labor availability and other factors. In addition, since the groundnut insurance and loan package is being used for some seed multiplication, groups such as ICRISAT could play a role in preserving the identity of the variety, helping to implement a system to insure seed identities are maintained.

REFERENCE SECTIONS

1. Design Illustration

In order to illustrate the design process, we discuss the example of the process of designing the 2006 Chitedze groundnut contracts. This discussion is not intended to be a complete documentation of the precise process undertaken, but instead it is an illustration of the main issues in a typical design exercise. The starting point for the design was a draft contract provided by the World Bank CRMG based on the 2005 Chitedze groundnut contracts. These were contracts using the 2005 phase payout function illustrated in Figure 3.1. The growing season of 14 dekads had been selected, split into three phases. The phases were set with phase 1 (dekads 1 to 3) designed to target the establishment and vegetative growth, phase 2 (dekads 4 to 8) targeting flowering, the most drought sensitive phase, and phase 3 (dekads 9-14) addressing pod formation to maturity.

The triggers and exits were calculated by approximating water requirements according to (CRMG 2005), with the triggers set to 60, 160, and 100 mm totals for phases 1-3 respectively and 30, 30, and 20 mm for exits. The sowing condition was calculated using the definition from (CRMG 2005) and set to 25mm. The contract price was 10% of maximum liability.

We began the contract improvement process with the WRSI model parameters, phase timing, sowing window, sowing trigger, triggers and exits from the CRMG draft contract but with the updated phase payout formula illustrated in Figure 3.2. We analyzed the performance of the contract against the weighted WRSI based loss index, with a target of obtaining a contract with a pseudo price rate of approximately 7%.

With the original triggers but the updated payout function, the contract had a high pseudo price of 12%, a low correlation to the weighted WRSI based loss of 34%, and a low payout rate of 16%, with 71% of the payouts occurring in the worst ¼ years of the loss index. Evaluated using historical yield based losses, the correlation was high, at 61%, with 50% of the payouts in the worst ¼ years.

We applied the optimizer directly to this contract, yielding triggers of 34, 161, and 99. Note that the optimizer did not substantially modify the second and third phases of the contract but instead improved the correlation while lowering cost by reducing coverage substantially in the first phase. The optimizer

was able to reduce the pseudo price to 8.5%, which was slightly above our 7% target. The correlation to the weighted WRSI based loss increased to 44%, with a low 11% pay rate and all of the payouts occurring during the worst ¼ years of the loss simulation. In essence, the way that the optimizer improved performance was to target the largest payment to the largest loss, and reduce the other payments. The correlation with the historical yield-based loss index changed to 53% with 50% of the payouts in the worst ¼ losses.

In order to understand how to move from this draft contract to an improved contract for the clients, additional stakeholder interaction was important. The key issues were to identify if the payouts would have been compatible with the drought stresses that the producers were concerned about and if the strategy of having few payouts that were highly targeted to the worst years of the simulation was one that the producers would find useful.

In addition to our discussions in farmer focus groups and other stakeholders, we presented draft contracts to ICRISAT experts in the Chitedze who had worked on the development of the variety. Discussions centered on the contracts allowed the experts to explicitly respond to contract strengths and weaknesses, providing an additional interaction focus beyond initial input based only on agronomic features of the crop.

In cooperative design meetings with farmers using the spreadsheet design tool described in Reference Section 10, several potential avenues for contract improvement were revealed. First, following an initial presentation of the phase payout formula used in 2005 (and illustrated in Figure 3.1), the farmers asked that a new phase payout function be used, sketching with their fingers on a printout of the spreadsheet design tool, and saying that the new function would better reflect the drought stresses they faced. The payout function they sketched was the updated function shown in Figure 3.2 that we had been planning to implement. Thus, the farmers illustrated their support for the updated function before having seen it.

The farmers said that they preferred more frequent payouts, and that although the crop had higher vulnerability in the middle of the season, dry spells were rare during that part of the season and they were more concerned about the more frequent dry spells that occurred later in the season. We discussed how to balance the coverage between parts of the season since it was not possible to cover both early and late season risks fully with an affordable premium. The resulting design choice was to include a large deductible, catastrophe oriented coverage in the first two phases, with little coverage for most years, but full payouts for very dry years combined with a lower deductible coverage for the third phase, with frequent, but smaller payouts.

Following these discussions, as well as design discussions with agronomic experts, we shifted the phase timing slightly, moving the border between phases two and three so that phase two ended earlier by two dekads, with those two dekads moved to phase three. Thus, the new timing was phase 1 (dekads 1-3), phase 2 (dekads 4-6), and phase 3 (dekads 7-14). This had the benefit of shifting some of the risk from the last part of the more sensitive middle phase into the last phase where we intended to target more coverage.

We ran the optimizer with these phases, and an initial guess that was based on the design strategy of a high deductible in the first phases and a low deductible in the final phase. A variety of initial guesses were explored. For this illustration we look at the example of running the optimizer with an initial guess of 40, 40, and 100 for the triggers, which yields a tuned contract with triggers of 34, 39, and 210. In this contract, the majority of the payments occur during the last phase, the correlation against the WRSI based loss is 57%, 100% of the payouts occurred in the ¼ worst losses of the index, and the pseudo price was 7%. The payout frequency was 17% which fell outside of the stakeholders' desired range of 20 to 25%. The correlations with historical yield based losses did not raise any alarms, at 53% correlations and 33% of the payouts in the worst ¼ years. Thus, a different and improved local optimum was uncovered by testing the alternative risk protection strategy developed with stakeholders.

Following the computer tuning, we manually adjusted the triggers to increase the payout rate slightly and to round off the trigger levels to multiples of 5. This yielded the final contract that was implemented in 2006 with triggers of 35, 35, and 220, a payout rate of 20%, an acceptable pseudo price of 7.6%, a correlation with the WRSI based loss of 0.55 and 78% of the payouts occurring in the worst ¼ years of the loss simulation. The majority of the historical burn payouts were due to the last phase. This contract also performed well against the historical yield based losses, with a correlation of 0.66 and 50% of the payouts in the worst ¼ years. For maize in Chitedze, sowing triggers didn't need tuning because failed sowing events were extremely rare, not occurring at all in the historical record.

Although this contract meets its design criteria quite well, it is likely that it could be further improved in the future through additional analysis supported by continued interaction with stakeholders and experts as they gain experience with the insurance product. It is important to build local capacity to allow the continual adaptation and improvement of contracts. For additional activities likely to yield improvements in contracts, refer to the section on design issues that must be addressed in the future.

2. Overview of changes from original design

The original contracts were directly determined using the WRSI model based calculations presented in (CRMG 2005) with insurance contract parameters phrased in terms of WRSI features. Although original contracts were verified through analysis of historical rainfall and correlations with observed yields and WRSI simulations, design responses in the original contracts were not as transparent as they could have been. A systematic parameter update process was not explicit in the original design process. Since contract parameters were phrased directly in terms of WRSI model parameters, climate or data driven updates of model parameters were awkward.

Much of the protection that an insurance contract provides is climate driven, not crop vulnerability driven. In fact, if a farmer is using a crop that is well suited for the local climate, the crop will be selected so that its periods of drought vulnerability coincide precisely with the times in the season that are likely to be wet. Likewise, the crop will be selected in order to have low water stress vulnerability during the parts of the season that are typically dry. Therefore drought vulnerability is a balance between the particular strengths of the crop and the water stress challenges presented by the local climate and a drought protection contract must explicitly address this balance in its design. In addition, since no

model (including WRSI) would be expected to have perfect accuracy in predicting crop water stress, it is important to allow for imperfect model precision in the design process instead of providing an inflexible link between model parameters and final insurance products.

In addition to the challenge of accurately reflecting drought stress, insurance contracts embody constraints that are not embodied in crop models or rainfall and yield data. An insurance contract must be functional as a financial product. This is particularly true for microfinance products, which must be highly cost effective and straightforward to transact, providing a very useful product for the client for a low premium. A fundamental feature of index insurance is that there are many losses that it does not cover. Therefore, the tuning process for index insurance contracts involves selecting what losses the index is able to most cost-effectively address at the expense of those losses that the index does not address well. Though it is possible to design a contract that addresses a wide range of losses with an unlimited premium and a high payout frequency, the need to create affordable and workable contracts requires making sacrifices in coverage in order to target the index to losses it handles most efficiently.

Because these products offer partial coverage (as opposed to a traditional comprehensive insurance product) at affordable rates, the design process must address the problem of how to target the parts of potential losses that can be insured most cost effectively given price and other product constraints. Insurance products cannot be too expensive. Since comprehensive coverage is typically prohibitively expensive in the microfinance context, contract design is not a question of how to cover all the risk, but instead how to budget a farmer's premium in order to most effectively address as much risk as possible in the most useful way for the farmer. Insurance cannot pay out each year while a policy that pays out with only a 5% probability may not be a useful risk management tool for a farmer. Deductibles and levels of risk retained by the farmer must be adjusted to arrive at a product that has an implementable payout frequency. Trade-offs must be made between deductibles for losses from potential drought stress from different parts of the season. It is therefore important to have a process that can systematically and explicitly address these issues in contract design.

Since the design process for the original contracts did not provide explicit mechanisms for systematic inclusion of climate features, uncertainty levels for drought stress, or economic factors and insurance product constraints, we extended the design process to more formally address these issues, described more fully in the following sections.

3. Changes in phase payout function

We simplified the formula for payouts based on phase rainfall totals in order to increase the transparency and robustness of the product. Figure 3.1 depicts the structure of the 2005 formula. Phase rainfall totals above a particular level (the trigger), warrant no payout. If the rainfall total is below the trigger, but above the exit, payments increase from zero linearly, with a slope determined by the "ticks" specified for that phase of the contract. In the 2005 contracts, these ticks were determined directly from WRSI parameters, and triggers were selected as a particular level of loss as represented by the WRSI calculated water demands. If the rainfall total was below the exit (which was selected to represent 50% of WRSI determined demand), the maximum payout is awarded. Therefore a 1 mm difference in rainfall totals



Figure 3.1 2005 phase payout function

can change payments by orders of magnitudes. This was a critical issue for the particular contracts implemented in 2005, because the 50% WRSI level extremely unlikely in those locations. Although 50% WRSI as criteria has been used as an approximation for large scale crop failures, it is only an approximation at best.

The 50% WRSI criterion is only a rough distinction useful for rough categorization of stress levels and does not reflect agronomic processes leading to sudden change from a stressed crop to a complete failure. This feature was not evident in any of our process based crop simulation analysis. In addition, in our initial focus group meeting with farmers for which we discussed a draft version of the contract communication tool based on the 2005 contracts, the first feedback that farmers provided was that

they felt the discontinuity at 50% WRSI did not reflect their crops' water stress characteristics.

Because this formula leads to payouts that might be highly contentious if rainfall is near the exit, a dramatic discontinuity between potential maximum payout and the majority of payouts, and is only an approximate reflection of total failure level, the 2006 contracts eliminate this discontinuity.

In the formula for a 2006 phase payout is a piecewise linear function with no payouts if the sum is above the trigger, a maximum payout if the sum is below the exit, with a linear payment function ranging from no payout to full payout between the trigger and exit. This function (presented earlier and illustrated in Figure 3.2) is below.

Payout= (1 - (Rainfall Sum - Exit) / (Trigger - Exit)) Max Payout

As discussed earlier, since agronomic features of the crop are but one component of the risk that the insurance targets, the derivation of triggers and exits directly from the WRSI model is no longer pursued, particularly since the lower trigger of 50% WRSI does not accurately reflect full crop loss. Although individual plants can die from water stress, it is unlikely that all of the plants in a plot will die at the same time. Instead, the failure will be for an increasing fraction of plants across the plot as drought levels increase. The critical point at which the harvests are a failure is determined by the yield level at which it is not worth the farmer's labor to harvest the weak yields. Failure is a com-



Figure 3.2 2006 phase payout function

plex process, involving subtle agronomic features as well as economic characteristics of the particular farm family.

The exit is not easily determined scientifically to coincide with complete loss, but functions better when interpreted in terms of a parameter to use to target insurance coverage as cost effectively as possible. Thus, it is recommended that the triggers and exits be determined through the design process described in this document that begins with agronomic features, but where the final contract parameters represent a combination of agronomic features, climate, and economic constraints instead of only agronomic parameters.

4. Discussion of crop stress methodology

The role of a water stress model differs according to its application. A model that effectively quantifies and targets relative water stress events may have low skill at forecasting absolute yield levels, or quantifying the absolute level of risk a producer faces. In understanding the recommendations and comments we make, it is important to understand that the task at hand in designing the index insurance is not to accurately predict yield levels for a particular farmer, but instead to identify the most important water stress mechanisms for the community of farmers in the region surrounding a met station.

A WRSI algorithm that was based on dekadal precipitation sums and a constant water stress parameter was used to design the 2005 contracts for Malawi groundnuts. The algorithm used is described in (Commodity Risk Management Group 2006). In order to gauge the performance of the WRSI stress calculations, we have performed a battery of comparisons for groundnuts and maize in Malawi at the stations for which sufficient data existed to perform comparisons. We considered alternate WRSI



Figure 4.1 DSSAT crop yields and dekadal and daily WRSI based crop yields using average and 4-stage Ky values for Chitedze groundnut crop.

specifications and process based agronomic modeling to understand what the most appropriate specification and roles are for the modeling tools.

We considered two types of WRSI formulation specification choices in terms of their implications for contract design. The first was the use of daily rainfall as opposed to ten day dekadal totals to drive the model. The second was the inclusion of a seasonally varying yield stress parameter as opposed to one that is constant over the season. In addition, we investigated the utility of a process based crop model (this model is described in Appendix 5) in the context of contract design, and as a frame of reference for discussion of WRSI alternatives. The unweighted WRSI based specification only models stress based on the water processing features of the plant and soil in response to climate. For a given leaf area and root depth, the unweighted WRSI based model will yield identical stress for a plant facing the same amount of available water during a time when the plant is particularly vulnerable to stress and when the plant does not require any water. This is particularly important for a crop such as maize, for which there are particular parts of the growth cycle when water stress has much higher impacts on the plant.

Figure 4.1 illustrates alternate modeling specifications for water stress calculations of groundnut crops in Chitedze. WRSI based Crop Production Index (CPI) results are shown for daily and dekadal specifications with both seasonally varying and constant crop stress parameters (Ky). The WRSI based CPI ranges from 1000 indicating no stress and 0 complete water stress. Also included is a DSSAT process based yield simulation, which is presented in terms of kg/ha and normalized to have maximum yields of 10,000 kg/ha. The analyses are summarized in Table 4.1.

Dekadal summation of rainfall can reduce the stress represented in the model. In a dekadal summation, having the same amount of rainfall evenly spread over ten days is equivalent to having no rainfall for nine days and the last day with all of the rainfall for the period. Because of this averaging, we can see that in this case the dekadal calculated indexes under-represent yield stresses, with the indexes based on daily rainfall reflecting more stress with more variation. Therefore we recommend that if daily rainfall is available, it be used in the WRSI calculations.

Comparing the non-varying Ky results to the Ky parameters that vary by crop growth stage, we can see that drought stress in this example is less when the varying Ky is applied. It is likely that this is because the varieties have been well selected for the local climate, i.e. that the crops are more resistant to drought stress during the parts of the season that are typically dry. In order to capture the risk impacts of variety choice in the index design, we recommend that an index based on seasonally varying Ky be used for contract development. In terms of index design, there is some similarity between all of the WRSI based indexes, with most of the worst years in any WRSI based index being evident in the alternate specifications. The primary difference is the relative magnitude of alternate stress years.

For completeness, additional simulation results for the different stations and crops are presented without discussion in Appendix 9.

	<u> </u>	0 1			
	DSSAT Crop Yield	Dekadal CPI (av Ky)	Dekadal CPI (4 Kys)	Daily CPI (av Ky)	Daily CPI (4 Kys)
Min	0	690	777	650	735
Max	6285	1000	1000	1000	1000
Average	4270	923	947	872	911
STDEV	1375	79.2	58.0	78.0	58.1
CV	0.32	0.09	0.06	0.09	0.06

Table 4.1 Statistical comparison of DSSAT crop yields and dekadal and daily WRSI based crop yields using average Ky and 4-stage Ky values for Chitedze groundnut crop.

The DSSAT yield simulation provides a different picture, with much more variation and many differences in which years appear to be severe. Process based simulation models are highly sensitive to parameter assumptions and require a great deal of data. Assumptions can have dramatic impacts on simulation results. Many of these important assumptions are not known for the population or may need to be specific to each farmer (such as soil nutrient levels). Without extensive data for calibration, it is difficult to know if a process based model is representing a



Figure 4.2 EPA historical groundnut yields for Chitedze/Liongwe area.

representative farmer or a very particular hypothetical situation.

Since index insurance is awarded using a regional met station using a single contract for a population of farmers, index insurance is a tool best suited to target the covariate risk faced by a population of farmers. Other strategies are typically coupled with index insurance to target the idiosyncratic risks. These individually tailored risk management tools include such as crop diversification, risk reducing production practices, or pooling farmers and plots. In Malawi, farmers are pooled into groups in order to spread idiosyncratic risk. Another example is in Tanzania, where which farmers reported managing multiple plots at different elevations in order to reduce risk.

Figure 4.2 illustrates the covariate and idiosyncratic variability in yields with historical yield data at the EPA (sub district) level for groundnuts in the Chitedze/Lilongwe area. In this figure, one can see that there is covariate risk that impacts all of the sub-regions with EPA specific differences in yield. Table 4.2 reports the correlations between these EPAs, showing that although the covariate risk is relatively high for most regions, e.g. 1992, there is a substantial amount of idiosyncratic risk that must be addressed through other risk management tools.

Table 4.3 reports the correlations between WRSI based production indices, DSSAT simulation runs, and historical yields. WRSI based indices

Table 4.2 Correlations between individual EPA historical groundnut yields and average historical groundnut yields for the Chitedze area.

EPA Name	Correlation with Lilongwe Average
Chilaza	0.78
Demela	0.92
Kambanizithe	0.78
Ming'ongo	0.69
Mlomba	-0.52
M'ngwangwa	0.69
Mpingu	0.74
Nthondo	0.89
Sinyala	0.81
Ukwe	0.89
Mlomba M'ngwangwa Mpingu Nthondo Sinyala	-0.52 0.69 0.74 0.89 0.81

constantly have higher correlations with historical yields than the DSSAT runs. The correlation between DSSAT and WRSI varies by location and crop. It is possible that the DSSAT results are calibrated to a very specific and idiosyncratic situation. Therefore, we recommend that WRSI based stress indices be used to target the covariate risk as the benchmark index for contract design and that process based models be used (when available) to test the robustness of contracts as well as to help answer specific questions about crop behavior.

			2 2 0	1
Station	Crop	DSSAT/ hist. yields	WRSI/hist. yields	DSSAT/WRSI
Lilongua	groundnut	0.13	0.31	0.54
Lilongwe	maize	0.17	0.38	0.39
	groundnut	-0.01	0.39	-0.04
Kasungu	maize	0.37	0.77	0.04
Nkhotakota	groundnut	0.10	0.35	0.54
ΙΝΚΠΟΙΔΚΟΙΔ	maize	-0.22	-0.06	0.46
	groundnut	0.30	0.52	0.57
Chitedze	maize	0.01	0.24	0.28

Table 4.3 Correlations between WRSI and DSSAT simulated yields and historical yields for groundnut and maize crops.

In summary, the analyses and comparisons lead us to recommend that contract design be based on a WRSI based drought stress benchmark and that the WRSI stress modeling always be supplemented with alternate information sources for contract validation. We recommend that daily rainfall data be utilized in the WRSI model so that the implications of variation within a ten day period not be masked in the contract design process. We also recommend that a time-varying yield stress parameter be utilized, since critical water stress features are not addressed by WRSI without this parameter. We do not recommend that more detailed process based models, such as DSSAT be used as the design benchmark. Instead, we recommend these models be used (when available) to perform specific analyses to provide insight into particular design questions. The process based models not only requires a lot of data, but tend to be very sensitive to the calibration assumptions, leading to dramatic changes in simulated stress for small changes in model parameters that are not well measured, or that vary over the population of growers. Because contracts must be a compromise that addresses a wide range of farmers with different characteristics within a region, it is worthwhile to have a model that reflects the shared response to drought as opposed to the idiosyncratic parameters of a particular grower. When available, DSSAT models are likely to be useful in testing the effectiveness of a WRSI based contract to uncover drought stress features that have been missed by the WRSI model.

The WRSI water stress model is best interpreted in the contract design as a precipitation accounting system that is adjusted to represent the particular water stress characteristics of a particular variety. Its outputs are a direct representation of the assumptions that are used in the model. It is a well known framework, with intuitive parameters that can be transparently adjusted to reflect observed crop behavior.

Thus, it is well suited to contract design because it can be tuned and adjusted to most accurately represent characteristics of a particular variety in a given locality. Agricultural experts can typically provide input to enable the model to be tuned appropriately for a local crop. In addition, a model that is incorrectly calibrated is often easily recognized by local experts. The calendar for growth phases is explicitly assumed, which allows for verification with local experts as well as farmers. When discrepancies are observed, through discussions with agronomists or farmers, it is relatively straightforward to adjust the parameters to accurately reflect the timing of local varieties and techniques.

The information supplied by farmers is of particular importance in determining an accurate timing of the season: when a farmer sows and when the crop is in each stage of growth. WRSI assumes the timing of the season; therefore, in the case of an incorrect assumption, the insurance no longer serves its purpose, since its payouts would no longer correspond to true times of crop loss. For this reason, it is best to use a suite of tools in order to mobilize all the information available to ensure a well-designed contract. We used the following questions in discussions with farmers to verify and adjust WRSI parameters and contracts. The questions below are tailored to maize. An extended questionnaire is included in Appendix 7.

- What are the best years and the worst years for maize production that you can remember?
- What made these years the best and worst years? What were the specific events that caused yield to be good or bad?
- Does the dynamic sowing period reflect your sowing practices? i.e. do you wait for the first rains to sow?
- How do you judge when rain is sufficient for planting?
- What do you do if rains are insufficient for planting? Plant a different crop vs plant anyway etc?
- Are sowing and tasseling the two times when you feel that your crops are most vulnerable to drought?
- If there is a different part of the growing season in which your crops have been vulnerable to drought, what is this part, what month(s) does it occur, and in what years has it been a problem?
- In which years did you have yield problems because of drought, and for each year, what was the reason for the problem (e.g. dry sowing/weak start of rains or drought during the filling phase)?
- Do the historical payouts from the contract we are discussing match the years in which you would have expected a payout?

5. Loss proxy

In developing a loss indicator, it is important to recognize that insurance is a product that does not provide payments in most years. Therefore, the optimization task is not to design a policy that has high protection against all production changes, but instead to provide a contract that is well designed to efficiently address the more substantial losses. Insurance requires a deductible. That is, until a loss becomes substantial, there is no payout. Insurance is not a product that should "protect" a farmer from reductions to the maximum possible yield, and in fact must have no payment in the majority of years. It is important to acknowledge this feature in the optimization and evaluation of insurance. Basis risk is not simply the correlation with yields--it is the protection against losses of the size it is intended to protect against If the insurance is evaluated and designed using data on minor yield fluctuations in good years (which are by definition, the majority of years), but constrained to provide zero payouts in those years, it will falsely appear to have low correlations and will not be tuned to effectively cover the losses it is intended to cover.

In order to have an optimization criterion that leads to more effective insurance products, a proxy for losses is developed from the yield index. First, yield indicator data are multiplied by an approximate factor to convert them into the rough order of magnitude of monetary units. The exact magnitude of this factor is not critical, since the contract being developed is scale independent.² A rough benchmark level is selected for the level of yields below which a loss is indicated. Any yield level above this benchmark is not considered in the insurance design. The precise level of this benchmark is not critical; its main purpose is to shift the optimization and evaluation of contracts to losses, as opposed to good years. For transparency, the designs used in this project utilized the mean as the loss benchmark. This is a trade-off between how much yield information to offer to the optimization and evaluation process verses how much of the unhelpful information related to good years to remove from the process. The loss proxy is zero for all data points that are above the benchmark, and it is the benchmark less multiplied yield indicator data for points below the benchmark, leading to a loss proxy that is zero for all good years, and a positive loss value for years below the benchmark.

6. Optimization

The optimization algorithm adjusts the triggers of the contract to achieve the lowest variance in the simulated difference of payouts and losses for a given insurance price constraint. Since it is only able to identify local optima, the optimizer may only serve as a local tuner. It is also important to note that this optimization process does not weigh all of the potentially important factors in contract design, and should only be used as a part of contract design. After applying the optimizer to contract design proposals, we then evaluate the tuned contracts against historical data and other data and models that are available. Once we have developed a satisfactory contract, we round the contract's triggers to whole numbers in order to maintain simplicity of contract presentation. The rounding process has negligible impact on contract performance, but results in contracts that may be easier to communicate. Contracts that are cast in terms of a high level of precision could mislead people to thinking the models were more precise than they are.

The R software is free and can be downloaded from the http://cran.r-project.org/. The optimization method used in our code is an implementation of the standard Nelder and Mead (1965) algorithm. This

²In some cases this factor can be used as one tool to adjust the weighting of the optimization function between a few large payouts and many small payouts. A larger factor will put more weight on fewer payouts and a smaller factor will put optimization weight on more, smaller payouts. This will only work in particular cases, as in general the optimization is highly insensitive to the scaling factor.

method uses only function values and is robust, working reasonably well for non-differentiable functions (http://cran.r-project.org/doc/manuals/fullrefman.pdf, p1123). This algorithm converged much more reliably than alternatives, including simulated annealing procedures.

In the contract analysis and optimization a "pseudo price" formula was utilized. It was in no way intended to be official, as the final price of contracts should be negotiated by the appropriate players. The pseudo price formula was chosen to offer a robust, standard, and transparent representation of the trade-offs in risk exposure to the insurance provider, to serve as a predictable gauge to compare the relative performance of similar contracts. Our calculation of pseudo price is the ratio of premium to the maximum liability, where premium is calculated as

Average payout + Loading * (Value at Risk- average payout).

In our analysis, we used a Value at Risk that is the 99th percentile as calculated by the R software and a loading of 6%. Since the distribution is likely fat tailed because there are never enough observations to properly determine the 99th percentile, this value may be biased. However, it still represents a measure of the risk in the distribution and functions as a simple and transparent index that allows the optimizer to select between contract possibilities. The loading of 6% for the Value at Risk typically differs from final pricing and is chosen by the insurer given his portfolio and required return on VaR. A value of 6% is chosen simply to indicate some element of risk margin. Price changes should only have a subtle effect, if any, on the contract evaluation process so long as the final insurance pricing is qualitatively similar. In Appendix 2, we provide additional description of the pseudo-pricing calculation and describe alternative pricing functions that were explored in the contract design process but not pursued for final contract design.

When official pricing is performed, it is possible that some of the contracts are inexpensive enough that it would be worthwhile to increase the price in order to offer an increased level of coverage. In these instances, the most likely route to increased coverage is through increasing exits, which would lead to increased payouts without impacting the timing or frequency of payouts. In cases where a particular vulnerability needs to be addressed, it may be worthwhile to increase some triggers, while decreasing others in order to maintain a reasonable number of payouts.

The pseudo price was calculated using historical rainfall for the contract design algorithm. This `historical-burn' analysis is transparent and particularly useful for identifying and addressing mismatches between the contract payouts and years for which payments would have been useful. However, it is only part of the analysis important for actual pricing of the contracts. Since historical data is typically only available for approximately forty years or so, it is likely that there are many events that would be important for pricing that are not well represented in historical burn payouts (such as 99th percentile events). In addition, prices could be dramatically and artificially impacted by a small change in a contract parameter (such as a sowing condition). If a 1mm decrease in a sowing condition would eliminate a nosow condition in the historical data, a historical burn price fall dramatically. This dramatic price change would not accurately reflect the price change due to change in the probability of a no sow event in future years due to the 1mm contract change. Therefore it is important to use Monte Carlo techniques to properly characterize rainfall probabilities for final pricing. Monte Carlo pricing would smoothly change contract prices as the distance between the no-sow condition and the historical events. For the future, it would be worthwhile to utilize Monte Carlo techniques in contract design (to supplement the historical burn analysis). Note that some Monte Carlo analysis and aspects of portfolio pricing was used by the parties who were involved in the final pricing of 2006 contracts.

7. Index Insurance Complexity

One of the principal differences between an index product and a traditional loss based product is that index insurance is most fundamentally a hedge, not a comprehensive product. Index insurance acts to minimize one element of risk, but does not function as a comprehensive product and does not cover all losses. This can best be communicated to potential buyers by keeping contracts as simple as possible, so that the farmer easily understands the details of the contract and can accurately gauge his or her own basis risk. It is critical that the farmer is able to adjust her risk management activities around the limitations and capabilities of the insurance. If the index is too complex, the client will not be able to use it as an effective part of the risk management tool kit, but may end up facing risks that are not addressed through other means, and may not even be anticipated.

A complex contract carries with it the concern that a client may misinterpret the contract as a comprehensive product that covers all losses. Therefore, increased complexity should only be justified through a demonstration of vastly improved performance of the contract. When a complex contract is designed, we should always evaluate if a similar quality of coverage could be maintained through a simplified and more transparent strategy. We should also remember that the more complex contract may provide effective protection against modeled losses but be difficult to adjust to effectively protect against actual losses, which may only be truly known by the farmer.

In traditional loss-based insurance, the insurance is inherently linked with losses by the adjustor. In designing index insurance, the designer assumes the task of linking the insurance to the loss. To do this the designer must find the most cost effective way to cover as much loss as possible, understanding that the contract will never serve as a method of addressing all losses. This is a crucial point to emphasize in teaching contract design to insurance company audiences, since most companies are not used to having to connect insurance to losses and many may lack the expertise necessary to do so.

The complexity of the contract is one of the trade-offs that an index insurance designer must weigh. For the current project, a three phase contract is used to model drought stress. This has the advantages of being transparent to clients and being adaptable to address drought stress features that sophisticated models may not capture with the disadvantage of perhaps being less correlated with loss than a more complex index. We use the three phase index to approximate the drought stress exhibited in the WRSI model, and then adjust it to meet client demands and insurance practicality. It is interesting to consider how the three phase contract compares to the WRSI model itself in contract performance.

Of course, direct comparison against the WRSI contract is unfair, since the three phase contract must meet a price constraint and a constraint on payout frequencies. In order to illustrate the trade-off involved in using the three phase contract, we adapted the WRSI loss index used as the benchmark in contract design into an alternative rainfall insurance index. In order to meet payment frequency constraints, a 'deductible' level was determined for the WRSI loss index. For any loss below the deductible, the payment function is equal to zero. To address the price constraints a coefficient was determined that would, when multiplied by the non-zero WRSI loss index values, lead to a premium equal to that of the three phase contract. The WRSI based index payment for each year would therefore be the non-zero loss index values multiplied by the scaling coefficient.

Table 7.1 compares the three phase contract to the WRSI based index payment using the WRSI loss index as the loss benchmark. Since the WRSI payments are merely a truncated and scaled version of the loss measure, this table is not a true comparison of the quality of coverage using the WRSI based payouts verses the three phase payouts, but instead illustrates coverage losses that are entirely due to price and frequency as well as the coverage losses when using the three phase approximation to cover the WRSI loss. Note that the percentage of payouts in the worst 1/4 of years is not reported for the WRSI based payouts since they are identical to the WRSI loss in this measure.

		3 phase		WRSI Based	
Station	Crop	Correlation	% pay in 1/4	Correlation	% pay in 1/4
Lilongwe	Groundnut	0.46	58.3	0.72	91.7
	maize	0.59	58.3	0.77	91.7
Chitedze	Groundnut	0.55	77.8	0.76	100
	maize	0.42	30.0	0.77	100
Kasungu	Groundnut	0.39	60.0	0.68	100
	maize	0.41	83.3	0.64	100
Nkhotakota	Groundnut	0.41	36.4	0.81	100
	maize	0.69	72.7	0.83	100

Table 7.1 Correlations of 3 phase and WRSI based contracts to WRSI simulated losses

One can see by looking at the WRSI based payments that the price and frequency constraints typically lead to a twenty to 30% loss in correlation while the three phase contracts typically lead to an additional loss in correlation of approximately 0.2 to 0.3. In addition, the payments of the three phase contracts are not entirely targeted to the worst losses, ranging from about 30% of the payments in the worst quarter of the years to almost 80%.

In observing the table, it is important to keep in mind that the contracts actually implemented were adjusted from initial contracts that were more closely correlated with the WRSI based loss because of stakeholder requests. For example, stakeholders requested payments be shifted strategically to specific parts of the season for which the WRSI model did not show the greatest vulnerabilities. These changes could have been driven by the alternate risk management tools available to the farmers. For example since the farmers grow multiple crops, it may be that risks during parts of the season are most cost effectively covered by revenues from an alternate crop, leaving the role of insurance for the gap between the risk handling in crop mix and the risks faced by the farmer.
They also could have been driven by inaccuracies in the WRSI model when compared to farmer production. Therefore, although the use of the more complex WRSI model, which cannot be calculated directly by the farmers, might lead to improved coverage, it might also lead to a less appropriate product.

This is highlighted in Table 7.2, which compares the three phase contract payouts to our constructed WRSI based payouts in terms of protection against historical losses. Note that for some indexes there were no payouts during the historical data series, since the payout frequency is low and the historical time series are relatively short. Thus comparisons cannot be made for crops in these locations (and results are listed as NA in the tables).³ Comparing the performance of the two contracts, it is not clear which consistently performs better against historical loss data.

Therefore, the choice of the complexity of an index depends heavily on the feedback received from

		3 phase		WRSI	Based
Station	Сгор	Correlation	% pay in 1/4	Correlation	% Pay in 1/4
Lilongwe	Groundnut	0.15	25	0.36	66.7
	maize	0.55	100	0.78	50
Chitedze	Groundnut	0.66	50	0.67	66.7
	maize	0.53	100	NA	NA
Kasungu	Groundnut	0.23	25	0.39	25
	maize	NA	NA	0.45	0
Nkhotakota	Groundnut	0.59	40	0.31	33.3
	maize	-0.38	0	-0.34	0

Table 7.2 Correlations of 3 phase and WRSI based contracts to historical losses

stakeholders and the role of the index insurance product. Often, simple contracts based on phases are useful for retail to farmers, allowing a transparent contract and simple adaptation based on farmer feedback. Likewise, model based indexes have been applied more often when the client is a government or NGO (for example for the national famine relief programs) in which the client can run the index model to ensure the product provides cost effective risk protection and in which the model represents most of the information that the clients have available about losses. Of course, these strategies depend on the demands of stakeholders in each particular situation. The trade-off between complexity and transparency should be weighed for each application.

8. Portfolio pricing

Index contracts and reinsurance could be designed to take advantage of regional and global climate features, since large scale climate processes typically lead to negatively correlated seasonal rainfall between regions. For example, an ENSO state that is associated with higher probabilities of drought in

³Recall that it is important to take conclusions based on historical yield data with caution, since the time series are typically much shorter than what would be necessary for statistical identification, they represent averages as opposed to individual farmers, the data is often in error, and the varieties, inputs, and practices often are different than for the crop being protected.



Figure 8.1 maize payouts from 1962 through 2005

to over 2,000 mm in the highlands and areas close to the lake's shore (Munthali 2003). Ninety-five percent of Malawi's annual rainfall occurs during one distinct rainy season lasting from November to April (Malawi Department of Meteorological Services 2007). The Inter Tropical Convergence Zone

(ITZ), Congo Air Boundary, Semi-permanent anti-cyclones, easterly waves, and tropical cyclones all influence rainfall patterns in the country.

Research carried out by G.K. Munthali et al. found that it is rare for drought to strike all three regions of Malawi simultaneously. In 55 years, drought was only found to affect all three areas of the country on two occasions. Munthali also found localized mild drought to be more frequent in Karonga, in the north, and Salima, in the central

region, than the other regions studied. Both Karonga and Salima are located near the shore of Lake Malawi, illustrating the influence of the lake on rainfall patterns (Munthali 2003).

Table	8.2	maize	pricing	for	ina	iv	idual	l stations
			1 0.	· · ·				

Station	Price
Chitedze	297
Lilongwe	316
Kasungu	564
Nkhotakota	323

Southern Africa is correlated with ample rainfall in the Greater Horn of Africa. On smaller scales, year to year climate processes often lead to rainfall occurring on alternate sides of a mountain range. Even when the location of rainfall cannot be predicted, an understanding of the negative correlations between regions could be used to reduce costs. We illustrate this potential using existing contracts for maize in Malawi.

Malawi's rainfall is largely influenced by variations in altitude and proximity to Lake Malawi, varying from 500 mm in low lying areas

> Table 8.1 Table of Spearman Rank Correlations between timing of payouts for paired stations.

		Chitedze
	Lilongwe	0.49
Kasungu	0.09	0.14
0.06	-0.19	-0.12

The rainfall distribution patterns across Malawi may have potential to lower the overall cost of the index insurance. For example, if a weather station in the north is measuring a rainfall deficit, while a weather station in the south measures normal rainfall, then a single insurance company covering farmers in both locations may be able to use the differences in rainfall to decrease the total risk they are covering at any

given time. This reduction of risk can allow for a reduction in premiums, as less money is needed to cover total risk. An additional source of diversification is that different sowing timing and crop varieties may be used in different regions, which could lead to vulnerabilities in different times of the season. Thus, the same dry spell may severely impact a region in which maize is in the filling growth phase but have no effect on yields in a region for which maze is in the maturation and drying stages.

The stations for which the index insurance contracts are currently written are all in the central part of the country, making it likely that there are not large variations in rainfall patterns. However, as it is difficult to precisely determine the boundary between northern and southern Malawi rainfall trends, rainfall patterns between some of the four stations may be great enough that premium reduction is possible. To illustrate the potential for strategic selection of negatively correlated sites to reduce insurance costs, we present



Figure 8.2 Premium price of portfolio contract for Lilongwe and Nkhotakota for assorted weights of each station.

the example of maize payouts in Malawi, focusing on the stations with negatively correlated payouts.

Visual inspection of payouts at the 4 stations studied reveals that payouts rarely occurred at multiple stations for maize (see Figure 8.1).

Two negative correlations are evident in maize payouts. The greatest of those was the correlation of -0.19 between Lilongwe and Nkhotakota maize payouts. The other negative correlation was -0.12 between Chitedze and Nkhotakota. See Table 8.1.

We apply a simplistic pseudo pricing of maize contracts to illustrate the potential for portfolio pricing. In the tables below, the prices are presented for individual stations and different set portfolios of stations. The insurance price is presented both through the average of prices, ignoring portfolio effects

Table 8.3 maize pricing using averaging and portfolio methods, and percent differences to be used in premium reduction of individual contracts.

Station	Price
All (avg)	549
All (portfolio)	400
% Difference	13.0
Lilon/Nkhota (avg)	400
Lil/Nkh (portfolio)	345
% Difference	13.7
Lilong/Chit (avg)	365
Lil/Chit (portfolio)	354
% Difference	3.11

(referred to as avg in the table) and as the simultaneous pricing of the stations allowing for portfolio effects.

By the law of averages, including additional policies into the portfolio should decrease the risk faced by the insurer, allowing premium prices to decrease correspondingly. However, with index insurance, contracts for an individual crop at an individual station are perfectly correlated, so risk is only averaged down as additional crops and stations are included in the portfolio. Of course, if these contracts are somewhat correlated, the risk will be reduced by less than if they were uncorrelated, and if the contracts are negatively correlated, the risk reduction would be more substantial. This is illustrated in the price calculations, for which a portfolio including only Chitedze and Lilongwe, which have correlated payouts, reduces price by only about 3%, while the portfolio including Lilongwe and Nkhotakota, which have negatively correlated payouts, reduces prices by much more dramatic amounts. Likewise, it is evident that including a larger number of stations reduces risk more, as the portfolio including all stations has a substantially reduced price.

It is possible to strategically design a portfolio in order to maximize risk reduction. To provide the simplest example possible, we illustrate through a portfolio including farmers at the Lilongwe and Nkhotakota stations, with a product priced using the standard deviation specification for the measure of risk (see Appendix XI).⁴

Figure 8.2 illustrates the premium per farmer for different participation levels at the two stations. The lowest premium results from a contract where 58% of farmers were located in Lilongwe and 42% of farmers were stationed in Nkhotakota. It is likely that farmers might be offered less expensive contracts and insurers may face less risk if attention is paid to portfolio price effects when upscaling the program. It may be that insurance that is not feasible in a particular region when that region is considered for a stand alone policy may become workable, and perhaps even be beneficial for other regions, when it is considered as part of a portfolio. Future work concerning this feature of insurance design would therefore be worthwhile to pursue.

9. Forecast and insurance

In order to illustrate the potential for forecast based insurance packages, we include a summary of preliminary research we are pursuing using internal IRI funding. Note that this work is preliminary and is likely to change as it develops. Additional background and details can be found in (International Institute for Applied Systems Analysis 2007)

We use a hypothetical case based on the contract for maize in Kasungu, Malawi, as it provides a clear illustration of the potential for integrating forecasts and insurance. We use ENSO phase as a basic forecast in order to clearly illustrate the forecast and insurance problem. Of course, ENSO is merely a starting point, and forecasts with higher skill would be expected to have more dramatic impacts than our exploratory ENSO based analysis. ENSO is a useful starting point because it is commonly used, simple, transparent, requires few assumptions to apply, is a measured index (as opposed to a forecast model), and its potential impacts have been mentioned by each stakeholder group in the Malawi insur-

⁴We utilize the standard deviation for this example instead of the 99th percentile because issues related to small sample size prevent us from providing a clear and focused illustration. For actual contract portfolio design, risk metrics focusing on the tails of the distribution should be used.

ance project. The rough consensus beliefs about ENSO among stakeholders is that El Niño years are more likely to be dry, and that La Nina years are more likely to be wet.

We consider the evidence for forecast based design resulting from a simple student's t-test, acknowledging that many of the assumptions that the test is based on may not necessarily hold (for example that draws are iid). Our intent is not to provide a definitive hypothesis test based on the t-test, but instead to discuss the evidence commonly available to a design expert.

We calculate insurance payouts if the 2006 maize insurance contract for Kasungu was applied to the historical rainfall data available during the period from 1962 to 2006. For the sake of illustration, we study a hypothetical implementation of the Malawi insurance contract for one acre of hybrid maize production using the prices, parameters, and constraints agreed to by the stakeholders.⁵

We partition years into El Nino, La Nina, and Neutral based on the ENSO category in October (when contracts are signed)⁶. Table 9.1 presents a series of student's t-tests of differences in payouts for years of differing ENSO states. Hypothesis testing is challenging given the small numbers of years available for analysis. ENSO impacts are subtle if not impossible to detect. All tests have p-values above the 10% level except for the test that La Nina years are less likely to have a payout than other years. The majority of p-values are in the 10-15% range, which would be unlikely to drive an insurance design expert to redesign the insurance product.

We ask if these subtle detections of differences between phases can have non-subtle impacts on the insurance implementation.

Although the student's t-test has only subtle detections of differences in payouts by ENSO phase, the mean payout values are recognizably different (see Table 9.2) with average payouts in El Nino phases being substantially higher than average, and average payouts in La Nina years being much lower than average. If farmers were to strategically purchase insurance based on ENSO phase over the time period for which the observed rainfall patterns occurred, the farmers could have undermined the fiscal stability of the insurance system by not purchasing in La Nina years.

Using the formulas applied in the 2006 implementation⁷, we calculate the 'historical burn'⁸ insurance price appropriate for each ENSO phase (reported in Table 9.2). Although the differences in historical burn payouts are only marginally significant at best, the insurance rate differs substantially across ENSO phases, with the prices appropriate for La Nina phases almost an order of magnitude lower than the prices appropriate for El Nino phases.

⁵Note that the implemented packages included a bundle of groundnut and maize. We present a hypothetical maize only package to allow for clear interpretation of results. We use maize as the example crop for our analysis because it is highly sensitive to water stress, represents varieties that have been relatively well characterized for agronomic modeling, requires a substantial investment in inputs, and historical data is available for alternative options.

⁶If the NINO3.4 sea surface temperature index was more than 0.5 degrees warmer than average the year was categorized as El Nino, 0.5 degrees lower, La Nina. The remaining years were categorized as Neutral.

We proceed to evaluate a set of alternate contract designs in order to understand the potential impacts of each strategy. In this exercise, our goal is to identify and illustrate potentially effective strategies that could provide a basis for design of an implementable product.

In a theoretical world, it is trivial to adjust the price of insurance based on new information. However, fundamental constraints must be assumed away in order to allow for price changes to not require novel design innovations when applied in practice. One key constraint is the absence of a resale option in most practical insurance contracts. Insurance differs substantially from derivatives, as derivatives are freely traded and can therefore continuously adjust to any information on markets or forecasts. Insurance, on the other hand, is negotiated at a single price between a supplier and large number of retail customers and typically cannot be resold by the end user. In addition, for micro-products, the interaction necessary to recruit and process paperwork for a changing number of customers is very expensive. Considering that the typical premium is only a few dollars, it is important to have efficient, long term relationships with customers.

We avoid modeling approaches that would lead to results that hinge on assumptions for which we have little information, instead basing our analysis on parameters and features observable from the Malawi index insurance implementation as much as possible.

We base the comparisons on an indicator of gross revenues that a farmer might enjoy in a given year. The gross revenues are calculated using information from the Malawi 2006 contract design process. The gross revenues for a given year (in MKW) are the difference between revenues and costs, where revenues are the yields in kg multiplied by the price of maize per kg plus any insurance payouts in that year. The costs per kg are the summation of the price of inputs, the insurance premium, and interest on the farmer's loan for inputs. For some comparisons we include an additional shadow cost of alternate uses for the farmland and labor.⁹

⁷Insurance price in MKW= Average(payout) + Loading * (Value at Risk -Average(Payout)). The Insurance price rate is the insurance price in MKW divided by the maximum liability in MKW. Note that although the loading and Value at Risk parameters we use were utilized in the design of the 2006 contracts, they are slightly different from the values used for the final pricing of the 2006 insurance. We use the pricing utilized in the design work of the 2006 insurance, which is a loading of 6.5% and a Value at Risk based on the 99th percentile.

⁸Historical burn pricing is performed by relying entirely on payouts determined from historical data, without attempting to characterize the underlying distributions. Although this technique may be overly simplistic, we utilize it for two reasons. First, it is highly transparent, because it does not require specification of distributional assumptions (except that the set of historical draws characterizes the entire distribution). Second, it was the pricing method used for determining the official price of the Malawi insurance.

⁹The price of inputs for 1 acre of maize is 3900 MKW and includes the cost of seeds and fertilizers for the management package recommended for the 2006 implementation. The interest was 27.5%. These figures were used in the 2006 package for calculating the package prices. The maize price is assumed to be 20 MKW/kg which was a representative price used for the designing the 2006 implementation.

maize prices are volatile and unpredictable partly because of the high level of government and NGO intervention in maize markets. Price risk is an important feature in the actual profitability of a real farm; it is a topic worthy of a separate study. To the extent that maize markets are closed and local production impacts prices, these fluctuations would dampen the ENSO impacts that we model. Instead of attempting to model this process, which would complicate our presentation without providing additional insight, we simply state this relationship and recommend that results be viewed with this possibility in mind.¹⁰

5 5 20	1 2 .	5 5 5	
Test	df	t	p-value
La Nina Payouts < Other years	37.7	-1.56	0.06
La Nina Payouts ≠ Other years	37.7	-1.56	0.13
El Nino > Other Years	14.5	0.69	0.25
Neutral > Other Years	42.0	-0.02	0.49
Neutral > La Nina	23.6	1.07	0.15
El Nina > La Nina	11.5	1.16	0.14

Table 9.1 Results of student's t tests of differences in payouts for years of various ENSO states.

Since the spirit of our analysis is to provide a basis for an implementable package, we build from the Malawi pilot contracts. In the Malawi index insurance implementation the insurance is bundled with a loan for inputs. The loan size includes the input costs and insurance premium.¹¹ Since the farmers typically do not have legal title to their land, the insurance is used to guarantee the loan by requiring the farmer to purchase insurance so that the maximum liability is equal to the loan size including interest. The package is unitary, that is a farmer can only purchase the entire package or nothing. The farmer cannot purchase partial packages or multiple packages. Without the loan, farmers are unlikely to have the cash necessary to purchase the insurance. Thus the intent of the insurance is to provide access to credit to the farmer by eliminating much of the risk faced by the bank due to a farmer defaulting because of drought. Missing markets are common in this application. In fact, the primary purpose of the insurance is to exist.

Instead of making the series of uninformed assumptions necessary to characterize farmer demand, we use the information that we do have in order to propagate the price changes through the insurance/ loan/input bundle. We rely on the consensus of design constraints for the Malawi package as revealing the intersection of contracts within stakeholder preferences. One of the key constraints imposed was that the insurance premium was below a maximum acceptable level. In addition, farmers were almost universally interested in larger loans while banks imposed the constraint that the loan with interest be equal to the maximum liability of the insurance. Therefore we use the cash price of the insurance un-

¹⁰Output price stabilization schemes (such as forward pricing) are typically built into micro finance index insurance bundles.
¹¹In addition, in the actual implementation a tax is included. To simplify our presentation we do not include the tax.

modified by ENSO as a constraint for the premium for all phases, and implement ENSO based price changes by adjusting the maximum liability, and therefore the respective loan size and budget for inputs. Thus, in a La Nina year, while a farmer would pay the same premium in cash as in the non-ENSO adjusted insurance, the farmer would be entitled to a larger loan, and therefore a larger budget for inputs.

Table 9.3 presents the elements of a package that is scaled to reflect an ENSO based insurance price. Holding the cash price of the insurance constant, the changing price leads to a maximum liability in La Nina years that is almost an order of magnitude larger than in other years. Referring to the Input Budget Weight row the budget available for inputs in a La Nina year is about seven times larger than in the non-ENSO adjusted package, with an El Nino budget approximately three quarters of the nonadjusted package.



Figure 9.1 Gross Revenue for Standard and ENSO adjusted insurance packages.

Consider a hypothetical farm that allocates its land between 'local' maize varieties and production practices and hybrid maize production under the input package recommended for the 2006 insurance product, with the allocation determined by the size of the budget available for hybrid maize production. The benchmark hybrid production level is determined by the budget for the ENSO based price, changing the acres necessary to expend the seed and fertilizer budget using the per acre levels recommended for the 2006 package.

	<i>J</i> 1		
El Niño	La Nina	Neutral	All
Insurance Rate	0.16	0.02	0.11
Insurance Price	4	160	1002
Mean Pay	984	108	574
Number of Payments	2	I.	3
Number of Years	12	11	22
Pay Frequency	0.17	0.09	0.14

Table 9.2. Insurance contract characteristics for each ENSO phase.

Without extensive calibration to observed yield, changes in crop simulations are unreliable to predict how changes in crop and input use are mapped into yields. For this presentation we utilize historical hybrid and 'local' maize production data to illustrate the potential for gains. Some of the primary caveats to keep in mind when interpreting the historical yield results follow. First, it is not known if the varieties or practices are the same as the ones utilized in the 2006 package. Second, they represent regional averages as opposed to the yields of an individual farmer, so much of the variation that an

J	1 8 8 5		1	
	El Nino	La Nina	Neutral	All
Insurance Rate	0.16	0.02	0.11	0.12
Insurance Price	703	703	703	703
Loan	3515	30916	4949	4603
Interest	967	8502	1361	1266
Input Budget		30213	4246	3900
MaxL	4482	39418	6310	5869
Input Budget Weight	0.72	7.75	1.09	I.

Table 9.3. Characteristics of a bundled package designed to reflect an ENSO based insurance price.

individual farmer faces will be averaged out. Third, there may be errors in their measurement. Finally, they are only available for a short time span, beginning in 1984.

We apply a series of conservative assumptions that would lead to lower benefit estimates if unrealistic. The price the farmer receives for both types of maize is assumed to be the same. The cost of inputs for the non-hybrid maize is assumed to be the cost of purchasing (or forgoing the sale of) market recommended seed at the sale prices that the farmer receives for maize. The quantity of maize seed planted per acre is assumed to be equal between hybrid and non-hybrid. The labor required is assumed to be similar between hybrid maize. If the labor requirements for hybrid maize are substantially larger than those for non-hybrid, the benefits of using the forecast would be attenuated.

Table 9.4. Revenues for Standard and ENSO adjusted insurance packages.

		1 0		
	Mean	Min	Max	Var
Standard	12978	6683	19932	14850031.83
ENSO based	37129	6565	152823	2584196785
ENSO/Standard	3	I.	8	174.0196125

The results of this analysis are shown in Table 9.4 and Figure 9.1 The mean gross revenues for the ENSO adjusted package is more than twice the non-adjusted package.

Although these package strategies outlined provide for a relatively stable customer base and amount of premiums delivered to the insurance company, they reflect potentially very different values at risk and changes in capital necessary for loans and potential insurance payouts that vary with ENSO state. These ENSO based variations could provide major challenges for the financial management of the insurance providers and lenders. In order to address this problem, insurance providers and lenders could simply purchase ENSO indexed insurance or options from re-insurance providers to stabilize finances, since ENSO impacts are oppositely correlated across different parts of the world. This provides a natural role for reinsurance companies and derivative markets in supporting local microfinance providers.

The results presented here depend not only on parameter assumptions, but also on the assumption that future seasonal precipitation will follow the same correlations with ENSO as the small number of historical observations that we have had so far. Given the low numbers of observations of ENSO states, it is often difficult to find strong statistical test results that imply that it is important to adjust insurance based on ENSO when historical burn analysis implies substantial impacts. Although we cannot guarantee that the future ENSO impacts will be the same, given the potential for strategic behavior and the potential risk management benefits one would have to guarantee that future ENSO impacts will not in any way follow the behavior of the past in order to proceed without designing ENSO impacts into the insurance package. The examples we have presented here demonstrate that even simple, crude, and conservative implementable strategies hold the potential for substantial gains through integration of forecast information into microfinance insurance packages, suggesting that refined approaches may provide greater benefits.

Clearly, the work presented is merely a starting point for forecast based insurance packages. Additional research using more sophisticated forecasts and better characterization of the underlying distributions, correlations, and skill would be valuable. Breeding programs and agricultural experiments could be integrated in this effort to build a portfolio of varieties that could take advantage of ENSO package strategies. Of course, for any actual implementation, cooperative research must be done with stakeholders and local experts in order to design truly effective and workable packages, addressing financing constraints and price volatility issues, and allowing stakeholders to negotiate packages that represent their own preferences.

10. Description of contract communication tool

In collaboration with Nicole Peterson of Columbia University's Center for Research on Environmental Decisions (CRED), we created contract calculators and Contract Communication Spreadsheets for each of the contracts developed. The Contract Communication Spreadsheet is a tool for understanding contracts in terms of money owed and loan reduction, complete with basic instructions on the sheet's use. Each contract presents the indices for each growth phase of the crop. The sheet begins with a section listing the size of the loan and the trigger and exit rainfall parameters for each of the crop's growth phases, including information about the sowing condition (Phase 0), which must be met for the other phases to begin (if not, the loans are paid by the insurer under a no-sow condition).

The Contract Communication Spreadsheet also includes a graph of the historical payouts for drought insurance contracts for their particular station to give farmers an understanding of the frequency that payouts occur, and to demonstrate that majority of years there will be no payout. Many of the important features of the insurance are listed on the sheet, such as the failed sowing rule, that rainfall is measured at the meteorological station and that individual fields may experience rainfall amounts differing from this measurement. Additional clarifications stating that most years farmers will not receive a loan reduction and that payouts will never exceed the maximum liability are also included.

The farmer is able to calculate her specific loan reduction using the information on the worksheet and the rainfall amounts for that year. Using the rainfall amounts for each phase, the farmer follows the instructions included in the middle of the worksheet. In brief, she measures the distance from the amount of rainfall received, listed on the Y-axis, to the line of insurance. This distance is then placed against a scale of currency at the top of the worksheet. The measuring process is carried out for each of the phases

to show the total loan reduction that has occurred as a result of insurance payouts throughout the growing season. Contract communication tools for each contract are included in Appendix 10.

When we presented potential contracts to farmers in this format, farmers immediately offered feedback that we then incorporated into the design of the final contracts. All farmers seemed to find the worksheet useful for calculating loan amounts, and for understanding the program. Farmer input in this regard, was critical in designing an effective contract that met farmer and stakeholder needs. This exchange demonstrates the effectiveness of this approach of contract presentation, as farmers appeared to clearly understand the insurance being presented to them.

The Contract Calculator Spreadsheet that accompanies the Contract Communication Sheet includes all the equations and data necessary to calculate the contract sheet. It includes a scenario section with parameters to set in order to determine the actual contract. This section of the calculator includes prices and amounts of individual inputs, typical yield size and harvest price, insurance tax and interest, as well as the insurance price and desired premium. Another section includes contract information, such as phase lengths, triggers, exits, tic size, sowing start and end dates, and the price of insurance. These two sections provide the information necessary to complete the calculated values section of the contract calculator, where total input price, insurance rate and tax, crop value, loan size and premiums with tax, and break-even points are determined per acre.

We also developed some training materials for those presenting the contracts in an attempt to fill some of the gaps in farmer understanding of the contracts. These materials focused on explaining rainfall measurements (rain gauges) and contract periods (dekads and phases), as these were two of the most confusing or new aspects of the program to farmers.

Together these sheets provide both an easy means of communicating contract design and function to farmers and stakeholders, while serving as potential educational tools to teaching some of the concepts and methods used in contract development.

CONCLUSION

In this report, we have described our project products to World Bank's Commodity Risk Management Group (CMRG) in the development and evaluation of index insurance contracts for smallholder farmers in Malawi, Tanzania, and Kenya. The development of some products we are providing was supported at no cost by the NSF-funded Center for Research on Environmental Decisions.

Following the project Terms of Reference, contracts were designed and evaluated for each country. Following the project specification, we have developed in depth analysis, such as process based crop simulations and quantitative analysis of historical data, for the Malawi case study. These additional analyses are unique to the Malawi case, which was selected to be the case study for more in-depth analysis.

In general, the contract development and evaluation process has led to a set of contracts that appear to perform extremely well. So much so, that demand in many places has overwhelmed administrative capacity to serve clients. As this is an unsubsidized product that is purchased by clients, its value can be seen in its market demand. Since thousands of loan/insurance bundles have been voluntarily purchased by farmers in Malawi, the price that they have paid provides a minimum bound on the value they place on the product. In interviews, farmers have stated that their primary strategy for adaptation to climate change is enrollment in the insurance program.

Much of this success is due to the outstanding input and support from project partners, including strong data and analysis support from the Malawi, Kenya, and Tanzania Meteorological services. Because of their wide range of competencies, it is likely that these Meteorological services could play a much expanded role in project scale up. It is important to ensure that mechanisms exist to provide resources for Meteorological agencies for the necessary data collection, cleaning, reporting, and analyses.

There are several issues that we addressed in evaluating and improving the initial Malawi 2005 pilot contract design process for updated contracts in Malawi Kenya and Tanzania. First, the initial Malawi contracts had particular features in the formulas that were modified in order to increase robustness, performance, flexibility, and transparency. Second, given the deterministic agronomic modeling focus in the initial Malawi contract design, it was important to extend the design process to include more statistical analysis to arrive at contracts tuned both to agronomic features of crops as well as climate

characteristics. We evaluated and improved the crop water stress calculation techniques to more effectively represent drought related risk in the contract. Since agronomic models have a finite level of skill in reflecting actual losses, and since each source of information about losses has limits in terms of reliability and accuracy, we developed a systematic design methodology that could utilize the strengths of each source of imperfect information. Finally, we provided formal mechanisms to incorporate financial constraints in the contracts.

It is important to keep contracts as simple as possible so that the farmer easily understands the details of the contract and can accurately gauge his or her own basis risk. The farmer must be able to adjust her risk management activities around the capabilities and limitations of the insurance. If the index is too complex, the client will not be able to use it as an effective part of the risk management tool kit, potentially ending up with the client not being aware of what risks she is still exposed to.

There are several important issues that have yet to be addressed in the design of future contracts, in order to ensure that the product evolves into a fully sustainable and scalable product. Perhaps the most important is to build capacity for local design and adaptation of contracts as existing needs change and new needs are identified. In addition, the design process must be updated in order to allow information in seasonal precipitation forecasts to be utilized in the insurance strategy. Crop breeding programs can be integrated into this process, leading to varieties that are adapted to play the best role possible in the bundled insurance/credit/forecast system. Contracts could be developed further to more elegantly address failed sowing issues and sporadic starts to the rainy season. Index contracts and reinsurance must be designed acknowledging regional and global climate features, since large scale climate processes typically lead to negatively correlated seasonal rainfall between regions. Work should be done to more accurately and transparently characterize the distributions underlying historical precipitation that lead to losses and payouts to bring design and pseudo-pricing beyond historical burn analysis to utilize Monte Carlo based simulation for improved characterization of risk. Techniques should be developed to interpolate information between stations and to use satellite based products. These, and related techniques should be advanced to enable a quality product to be established when a new station is installed. These techniques would be critical for other issues, such as detecting data tampering, reducing basis risk, and perhaps enabling the availability of index products where met stations are not available. It is worthwhile to utilize economic contract theory to develop incentives that discourage tampering and encourage accurate farm reporting. Contracts could be designed to reveal the value of insurance through market transactions. It is important to develop communication tools for cooperative design, education of contract issues, and exercises to test for farmer understanding of products. Indexes should be explored to cover additional risks, such as excess rainfall.

APPENDIX I. DESCRIPTION OF ALL CONTRACTS

Malawi contracts

Following the design process described earlier, the contracts designed for Malawi use the weighted, daily WRSI model in conjunction with the input from agronomists and feedback received from farmers and stakeholders. Experts from NASFAM, ICRISAT and Chitedze research stations were consulted, as well as agrometeorologists in the Malawi Met service. We participated in two cooperative design sessions with farmer groups. We evaluated and redesigned contracts using this feedback. In addition, contracts were evaluated against more complex crop models and historical data. The following tables present contract parameters for each of the contracts designed, as well as key indicators of contract quality, such as timing and frequency of payouts and the correlation between payouts and losses. Given the payment frequency of some of the contracts and the limited time span of historical yields, it was possible for a contract to have no payouts during the time span covered by yield data. For these contracts it was not possible to study the correlation between payouts and historical yields.

In Malawi, two crops were addressed, groundnuts and maize. Because groundnuts and maize have very different drought vulnerabilities, different strategies were used in the contract design. The drought sensitivity of maize is largely determined through the genetics of the variety selected. Maize is most sensitive to drought during tasseling and filling with some sensitivity during early establishment. Following tasseling and filling, the crop has very little drought sensitivity. The timing of these phases is determined almost entirely by the genetics of the crop. Therefore, the maize contracts were designed to target protection into the second phase, which was timed to cover tasseling and filling.

Groundnuts are more flexible in the timing of drought stress. If growth is stunted by drought early in the season, the plants will take advantage of rainfall that occurs later. In addition, historical dry spells often occurred late in the season, when the groundnuts were more resistant to drought stress. This is to be expected when a variety is well adapted to the local climate. The design strategy arrived at following discussions with farmers and agronomic experts was to target two types of risks with the contract. The first risk targeted was for relatively common but non-catastrophic events of yield reduction associated with the dry spells occurring late in the season. The second risk targeted was for protection from only the most severe events arising from the years with the driest spells in earlier parts of the season, which

would lead to catastrophic losses. The farmers very clearly communicated a demand for the mix of these two risks that could be covered with the premium price constraint.

Groundnut contracts for Malawi have low trigger levels in the first two phases, which is when the groundnut crop is most vulnerable to drought. Thus, the main purpose of these phases is to protect against a catastrophic event. The third phase of the groundnut contracts has a higher trigger, and is where majority of the contracts' payouts are most likely to occur. By the incorporation of the higher trigger in the third phase, this design allows farmers to receive smaller, more frequent payouts, a balance demanded by farmers and other stakeholders (see Reference Section 1). In the following figures, the y-axis is the loss proxy described in Reference Section 5: Loss Proxy and the x-axis represents the year of harvest.

Kasungu n	naize				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.413
1	15	50	30	Percent of Payouts in 1/4 Driest Years	83.3
2	68	80	30	Correlation (Historical Loss)	0.12
3	912	30	20	Percent Payouts in 1/4 Driest Years (Hist)	NA
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	NA
				Payout Rate	0.136

Figure A.1.1 Kasungu maize loss and payouts as determined using Daily, weighted WRSI



Figure A1.2 Payouts and historical losses for Kasungu maize crop



Kasungu Maize Historical Loss

Kasungu C	Groundnut				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.392
1	I3	40	30	Percent Payout in 1/4 Driest Years	60
2	46	40	30	Correlation (Historical)	0.234
3	714	190	20	Percent Payouts in 1/4 Driest Years (Hist)	25
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	0.07
				Payout Rate	0.227

Figure A1.3 Simulated losses and payouts for Kasungu groundnut contract



Chitedze maize

Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)
1	I5	40	30
2	68	125	30
3	912	25	20
Sowing Window	7	Sowing Requirement	25

FigureA1.5. Simulated losses and payouts for Chitedze maize contract

Chitedze Maize Loss based on Daily WRSI, seasonal KY



Figure A1.4. Payouts and historical losses for Kasungu groundnut contract



Correlation	0.42
Percent Payout in 1/4 Driest Years	30
Correlation (Historical)	0.099
Percent Payouts in 1/4 Driest Years (Hist)	0.528
Pseudo Price	100
Payout Rate	0.222

Figure A1.6. Payouts and historical losses for Chitedze maize contract

Chiledze Maize Historical Loss



Chitedze (Groundnut				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.549
1	I3	35	30	Percent of Payouts in 1/4 Driest Yrs	77.8
2	46	35	30	Correlation (Historical Loss)	0.664
3	714	220	20	Percent Payouts in 1/4 Driest Years (Hist)	50
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	0.076
				Payout Rate	0.2

Figure A.1.7 Simulated losses and payouts for Chitedze groundnut contract





Figure A1.8. Payouts and historical losses for Chitedze groundnut contract



Lilongwe maize

•			
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)
1	I5	40	30
2	68	130	30
3	912	25	20
Sowing Window	7	Sowing Requirement	25

Figure A1.9. Simulated losses and payouts for Lilongwe maize contract





Figure A1.10. Payouts and historical losses for Lilongwe maize contract

Percent of Payouts in 1/4 Driest Yrs Correlation (Historical Loss)

Percent Payouts in 1/4 Driest Years (Hist)

Correlation

Pseudo Price

Payout Rate



Lilongwe Maize Historical Loss

0.591

58.33

0.554

100

0.090

0.267

Lilongwe Groundnut						
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.464	
1	I3	40	30	Percent of Payouts in 1/4 Driest Yrs	58.33	
2	46	40	30	Correlation (Historical Loss)	0.146	
3	714	230	20	Percent Payouts in 1/4 Driest Years (Hist)	25	
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	0.068	
				Payout Rate	0.267	

Figure A.1.11 Simulated losses and payouts for Lilongwe groundnut contract





Figure A1.12. Payouts and historical losses for Lilongwe groundnut contract



Nkhotakota maize

Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)
1	I4	150	30
2	57	140	30
3	812	50	20
Sowing Window	7	Sowing Requirement	25

Percent of Payouts in 1/4 Driest Yrs72.7Correlation (Historical Loss)-0.376Percent Payouts in 1/4 Driest Years (Hist)0Pseudo Price0.115Payout Rate0.244

0.686

Figure A1.13. Simulated losses and payouts for Nkhotakota maize contract





Figure A1.14. Payouts and historical losses for Nkhotakota maize contract

Correlation



Nkhotako	ta Groundnut				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.409
1	I3	120	30	Percent of Payouts in 1/4 Driest Yrs	36.36
2	46	120	30	Correlation (Historical Loss)	0.588
3	714	240	20	Percent Payouts in 1/4 Driest Years (Hist)	40
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	0.047
				Payout Rate	0.244

Figure A1.15 Simulated losses and payouts for Nkhotakota

groundnut contract

Nkhotakota Groundnut Loss based on Daily WRSI, seasonal K



Figure A1.16 Payouts and historical losses for Nkhotakota groundnut contract

Nkhotakota Groundnut Historical Loss



Mchinji maize

Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.704
1	I5	100	30	Percent of Payouts in 1/4 Driest Yrs	71.43
2	68	110	30	Correlation (Historical Loss)	NA
3	912	140	20	Percent Payouts in 1/4 Driest Years (Hist)	NA
Sowing Window	7	Sowing Requirement	25	Pseudo Price	0.132
				Payout Rate	0.25

Figure A1.17 Simulated losses and payouts for Mchinji maize contract



Mchinji Gr	roundnut				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.283
1	I3	100	30	Percent of Payouts in 1/4 Driest Yrs	50
2	46	70	30	Correlation (Historical Loss)	NA
3	714	170	20	Percent Payouts in 1/4 Driest Years (Hist)	NA
Sowing Window	1117	Sowing Requirement	25	Pseudo Price	0.055
				Payout Rate	0.148

Figure A1.18. Simulated losses and payouts for Mchinji groundnut contract

Mchinji Groundnut Loss based on Daily WRSI, seasonal KY



Tanzania

In Tanzania, the crop insured was maize. The contracts were designed to cover maize grown during the long rainy season. Because the 3rd phase of the maize growing cycle is not associated with significant yield stress, stakeholders chose to eliminate that phase from the contract and a two phase contract was designed. For Tanzania we did not have information on historical yields or crop simulations, so contracts were designed using the WRSI based model, supporting documents (Technoserve 2006), discussion with agronomists, agrometerologists and feedback obtained in four cooperative design sessions with groups of farmers and local extension experts. In addition, remotely sensed approximations for PET were necessary, since local stations did not have the necessary sensors (see Appendix 4. Potential Evaporation). Because historical yields were not available, cooperative design meetings with farmers and agrometeorologists were relied upon heavily. The time-varying parameters and sowing conditions in the crop loss simulation were verified against farmer reported sowing dates and phenology, with slight adjustments made in the model timing. We participated in four cooperative design meetings with farmers. Contracts were adjusted to reflect farmer reported sowing dates and phenology and to target payouts more closely to drought stress years reported by farmers for the phase in which they reported stress. This exercise led to contracts that yielded higher correlations at lower costs than costs determined prior to the adjustments.

Insurance company stakeholders indicated a preference for less expensive contracts with similar payout rates to the contracts presented below. The prices of both contracts could be lowered while maintaining a similar payout rate by lowering or eliminating the exits and manipulating the payout for the no sowing

condition. The price of the Babati contract could be decreased by lowering the phase 2 trigger to 100, which would lead to a 20% payout rate and a premium of 4.6%, while continuing to payout in key years with a good correlation between payouts and losses. This change would likely not provide enough insurance to cover the entirety of the loan.

Mbulu is more expensive because of the sowing failure. Lowering the phase two trigger for Mbulu to 155 is another method of decreasing the price of that contract. When this is done, a correlation of over 50% between payouts and losses remains, and the price drops to 6.5%, while continuing to pay out in key years. This change does result in a decrease in payout frequency to 20%. Another possibility to lower the price of the Mbulu contract is through lowering the payouts for occurrences in the no sowing condition. All of the modifications suggested for decreasing the price of either contract are not due to efficiency gains but instead are simply offering less coverage.

Babati maize

Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.652
1	I4	80	0	Percent of Payouts in 1/4 Driest Yrs	60
2	59	120	10	Correlation (Historical Loss)	NA
Sowing Window	1620	Sowing Requirement	25	Percent of Payouts in 1/4 Driest Yrs (Hist)	NA
				P 1 P 1	

Figure A1.19 Simulated losses and payouts for Babati maize contract



Correlation	0.652
Percent of Payouts in 1/4 Driest Yrs	60
Correlation (Historical Loss)	NA
Percent of Payouts in 1/4 Driest Yrs (Hist)	NA
Pseudo Price	0.1
Payout Rate	0.385

Mbulu ma	ize				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.572
1	15	30	0	Percent of Payouts in 1/4 Driest Yrs	83.33
2	612	170	10	Correlation (Historical Loss)	NA
Sowing Window	1519	Sowing Requirement	30	Percent Payouts in 1/4 Driest Years (Hist)	NA
				Pseudo Price	0.1

Payout Rate

0.24

Figure A1.20. Simulated losses and payouts for Mbulu maize contractcontract



Kenya

In Kenya, contracts were developed for maize grown in the long rainy season. As with Tanzania, the contracts designed for Kenya also do not cover the final growth stage of the maize. Because the growing was very long, the phonological stages that had been addressed in the first two phases of the Malawi and Tanzania contracts were subdivided, leading to three phase contracts for Kenya with coverage that stopped before the final maturation growing stage. This allows for the isolation of more dry spells during the most vulnerable period of the crop's growth so that dry spells can be identified in phase totals in spite of the long season.

Historical yield data was not available. Farmer feedback was obtained by consultants using the discussion questions listed in Appendix 7. This information was reported in (Concept 2006). Direct interaction between contract designers and farmers would have been preferable, if possible

The development of contracts in Kenya was particularly challenging because of the very long season and relatively high levels of rainfall. Because the WRSI based water stress simulation did not detect drought sensitivity, we utilized a pseudo WRSI to yield a model with an enhanced response to dry spells. This enhanced sensitivity was obtained by applying a reduction factor for the water holding capacity parameter. Because the role of the WRSI based model in the contract design is to provide a relative ranking of drought related stress during the season across years, artificially enhancing the response of the model to water stress does not systematically bias the contract design. Its role in the design process is to provide a benchmark for targeting protection to the vulnerabilities that are relatively more important. By increas-

ing the sensitivity of the model, the relative vulnerabilities are amplified, allowing this targeting. The adjusted models would be inappropriate for any use in which absolute levels are important, as opposed to ranking relative risks.

It is critical to verify that these adjustments lead to models that predict actual drought based losses. It is entirely possible that drought stress is not an important risk for the farms being addressed. Since the drought risk in for the Kenya sites considered was so subtle that the WRSI based model needed to be adjusted to enhance risk, it is important that the stresses that they identify be verified using field information or interviews with farmers, and contracts adapted based on feedback. Implementation of these contracts should not occur unless the drought stress covered is verified to exist and be well correlated with model payouts.

Contracts are designed to provide the most cost effective coverage given a particular price target. Thus, a contract will not be less expensive in regions with less drought risk unless the price target is explicitly set lower. For the contracts in this report, the insurance is typically designed to only cover losses to a level that would be necessary to meet input costs. In scenarios for which losses may be small, it is important to verify that they are indeed larger than the payouts. This is particularly true for the contracts being designed for Kenya.

In this context of long seasons with high levels of rainfall, alternate strategies may be more effective than the three phase contracts. Insurance triggered off of dry spells may be worthwhile to investigate. Alternately, it may be preferable to focus on areas of Kenya that have more dramatic drought stress. The contracts developed for Eldoret and Kitale do perform well against the enhanced sensitivity WRSI simulations, so if the drought stresses can be verified, these locations have the potential for worthwhile contracts. The contract for Nakuru does not perform well, and additional information and design work would be necessary to arrive at a contract for that location. The project is currently exploring the possibility of alternative contracts and sites as it proceeds toward implementation.

Eldoret maize

Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.586
1	I4	300	0	Percent of Payouts in 1/4 Driest Yrs	80
2	510	500	0	Correlation (Historical Loss)	NA
3	6	900	0	Percent Payouts in 1/4 Driest Years (Hist)	NA
Sowing Window	1012	Sowing Requirement	80	Pseudo Price	0.053
				Payout Rate	0.185





Eldoret Maize Loss based on Daily WRSI, seasonal KY

Kitale ma	ize				
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.587
1	4	600	0	Percent of Payouts in 1/4 Driest Yrs	50
2	510	1200	0	Correlation (Historical Loss)	NA
3	1116	1500	0	Percent Payouts in 1/4 Driest Years (Hist)	NA
Sowing Window	812	Sowing Requirement	80	Pseudo Price	0.048
				Payout Rate	0.381

	Nal	kuru	mai	ize
--	-----	------	-----	-----

Nakuru maize							
Phase	Phase length (dekad)	Trigger (mm)	Exit (mm)	Correlation	0.254		
1	I3	300	0	Percent of Payouts in 1/4 Driest Yrs	37.5		
2	46	375	0	Correlation (Historical Loss)	NA		
3	712	750	0	Percent Payouts in 1/4 Driest Years (Hist)	NA		
Sowing Window	1012	Sowing Requirement	80	Pseudo Price	0.045		
				Payout Rate	0.25		

Figure A1.22. Simulated losses and payouts for Nakuru maize contract



Nakuru Maize Loss based on Daily WRSI, seasonal KY

APPENDIX II. PSEUDO-PRICING ALTERNATIVES PURSUED

This section provides additional background on the pseudo pricing algorithm and alternative specifications investigated in the design process. It is important to note that the alternative pricing specifications were not utilized in the final contract design. They are presented here only to provide a full reporting of the activities completed. The more sophisticated pseudo pricing strategies were not selected for several reasons. They were less transparent (and less easily calculated in tools such as excel). In addition, because many of the techniques were based on Monte Carlo draws, the identical contract would have slightly different prices each time it was evaluated unless very large samples were drawn. This meant that use of the alternative pricing strategies in the design optimization software was computationally very expensive without leading to contracts that were much different from simple and transparent pseudo pricing formulae. For the future, alternate methods of addressing the limited sample size issues would be worthwhile to pursue. Based on the experience of this project, it is recommended that simulations be performed for precipitation (as opposed to pricing) in order to utilize as much historical information as possible.

The price of insurance usually depends on the expected payouts from the product, and a loading factor or margin reflecting the insurer's preferences, their ability to handle risks, and the environment in which the operations take place. The later is sometimes referred to as the cost of risk. In practice, premiums are frequently obtained using the following formula (CRMG 2006), Premium=E(P)+Risk Margin, where E(P) denotes expected payouts and the *Risk Margin* is based on subjective considerations. For this work, the *Risk Margin* term was determined using the Return on Value at Risk (VaR) method. The VaRx is defined as the loss that will not be exceeded with x% confidence level (Hull 1998). In this framework, the risk margin takes the form,

Risk Margin = $\beta * (VaR_x(P) - E(P))$

where β , the "cost of VaR" (CRMG 2006) was set at 6%, and x at 99%. Hence the equation used to price the insurance is

$$Premium = E(P) + \beta * (VaR_{og} - E(P)) \quad (1)$$

The remaining parameters needed to determine the insurance price, namely the expected payout and the VaR are commonly obtained using either the historical burn approach, or by fitting probability distribu-

tions that are consistent with the observed payouts that would have occurred had the insurance been in place before. The distribution obtained through the later approach is then used to obtain expected payouts and the VaR at the desired confidence level through Monte Carlo analysis. For the historical burn approach, the parameters are obtained directly from the payouts that would have resulted if the insurance was in place in the past.

For the final contract optimization algorithm selected, the historical burn approach was used. Although this is likely to less accurately reflect the risks faced by the insurer, it is a more transparent and robust measure of trade-offs (as opposed to absolute levels). The goal of the design process is to provide a standardized pseudo price measure for the trade-offs in risk instead of precisely pricing the risk faced by the insurer. Upon completion of the design process, it is the responsibility of the financial partners involved to determine an accurate price for the final product using more detailed techniques. The advantage of using the historical burn pseudo price is that it is exactly repeatable (as opposed to a Monte Carlo based analysis) and transparent. It can be duplicated in less sophisticated software that is commonly available, such as Excel, without the need for extensions.

Because it is likely that the official price will exceed the pseudo-price, e.g. because of taxes and fees, it is important to design contracts with a pseudo-price that is below what stakeholders are willing to pay. For this application, the pseudo price of the insurance was obtained based on insurance rates, a measure of the price per unit of insurance (or protection). We first divide Equation (1) by the maximum payout (liability, L) of the insurance, to obtain

$$\frac{Premium}{L} = \frac{E(P)}{L} + \beta \left(\frac{VaR_{99}}{L} - \frac{E(P)}{L}\right) = r + \beta \left(\frac{VaR_{99}}{L} - r\right) = r + l \quad (2)$$

Equation (2) indicates that the insurance rate is the sum of the actuarially fair insurance rate r and a loading factor l. For the approach, per year payouts based on historical rainfall values were divided by the liability of the product. The resulting values (which by construction fall in the 0-1 interval) were then used to either fit a distribution to conduct the Monte Carlo simulations or to apply the historical burn approach to obtain the expected payout per unit of insurance r as well as the per unit VaR, Var_{gg}/L . After obtaining these values, the price of insurance is obtained by multiplying the loaded rate by the liability to get Premium=(r+l)*L.

Two different distributions (exponential and beta) were programmed in the code, as well as two different choices for the maximum payout, namely the liability of the contract and maximum payout that would have occurred based on historical data. The code also gives the user the option to use a different

$Premium = E(P) + \alpha \bullet \sigma(P)$

risk margin or loading factor based on the standard deviation of payouts. Under this alternative method, the resulting price of insurance is,

where α is known as the Sharpe Ratio, and $\sigma(P)$ is the standard deviation of payouts. The user has the option of changing both α and β from the VaR method.

The pricing functions encoded followed several steps to calculate pseudo prices. In order to make the function more general and less dependent on the actual units of the data, we work with the more commonly used insurance rates as opposed to actual values. Historical payouts are divided by the liability of the product. There is an option to divide by the maximum observed payouts, if deemed more appropriate for the application at hand. The resulting vector will contain a series of zeros and a series of values between zero and one.

When the historical burn method is used, both the statistics needed for the pricing described above are obtained directly from this vector. When Monte Carlo analysis is used, there are different options to fit two different distributions to the nonzero payouts from this vector. Two distributions, frequently used in practice for insurance pricing were coded. Given that the values of non-zero payouts will be contained in the zero-one interval, and the probability density function (pdf) of positive payouts usually has a downward slope, we selected the beta and exponential distributions. The beta distribution is strictly contained in the 0-1 interval, and has the flexibility to reflect different distributional shapes, including a downward sloping pdf. The exponential function is very simple to fit, and also has a downward sloping pdf. The values of an exponential are not confined to the zero-one interval, but for most applications this would not cause any problems. In applications, in which the fitted exponential parameters might result in sampling values greater than 1, the code will discard the value and replace it with a one. If this occurs frequently, it may be more appropriate to use the beta distribution option. Other distributions could be easily coded into the function.

Once the parameters for the distribution are fitted (the code does it through maximum likelihood), they are used to obtain a large sample of positive payouts per unit of insurance. The payouts are placed in a vector with a number of zeros, in a way to maintain the proportion of zeros and positive payouts observed in the original data. Note that the function restricts the simulated data to have the same proportion of zeros and nonzero values as the original data. The average of this vector is the expected insurance rate introduced above. Both the VaR (at a user specified confidence level) and the standard deviation per unit of insurance are obtained.

The function then returns the loaded premium rate for the sharpe ratio, and Return of VaR (outlined above for both a user specified confidence level and by replacing the VaR by the maximum historical per unit payout), using the values of α or β selected by the user. To obtain the final premium the loaded rate must be multiplied by either the liability or the maximum observed payout, depending on which was used to normalize the payouts initially.

Monte Carlo analysis based directly on rainfall levels (as opposed to the limited dataset of historical burn payouts) is likely to be worthwhile in better characterizing the risks faced, and we therefore recommend that this be pursued for future contract design processes.

APPENDIX III. VARYING YIELD STRESS IN WRSI BASED LOSS CALCULATIONS

The WRSI model used in the development of the initial Malawi contracts was an un-weighted, dekadal model, described in detail in the WRSI appendix of the Terms of Reference for this project. Standard, un-weighted, WRSI is calculated by determining the ratio of actual to potential evapotranspiration of a crop over each time period. From this, crop yield is estimated using an equation where a single crop coefficient (Ky) represents the seasonal yield-response factors of that crop. Standard, un-weighted WRSI is calculated using the equation:

$$WRSI = \frac{\sum_{i=1}^{n} ETa_i}{\sum_{i=1}^{n} ETp_i}$$

where *ETa* and *ETp* represent the actual and potential evapotranspiration of the crop over a time period i. The final WRSI from the end of the season is then used to calculate crop yield, using the following equation:

Crop Yield = 1 – (1– WRSI)* seasonal Ky * Maximum Potential Yield

The single value of allowable water deficit (Ky) used in this equation is determined by averaging the crop's water requirement for the entire growing season. Since a crop's response to water deficit varies depending on what stage of growth it is in during the period of deficit, the single Ky value does not adequately represent a crop's water requirement throughout the growing season. Similarly, the length of the dekad does not adequately capture fluctuations in crop-response to rainfall deficit.

After estimating the variables used to generate WRSI, the relative crop yield (RY), which reflects the varying crop water stress vulnerability, is estimated using the following equation:

$$RY = 1 - \sum_{i=1}^{n} \min\left(\left(1 - \frac{ETa_i}{ETp_i}\right) Ky_i, 1\right) w_i$$

where Ky is the Ky value for the day i and where w is the daily weight, introduced to incorporate the daily importance of "Ky" in crop yield estimation and calculated as

$$w_i = \frac{ETp_i}{\sum_{i=1}^{n} ETp_i}$$

APPENDIX IV. POTENTIAL EVAPOTRANSPIRATION

In the contract design, dekadal potential evapotranspiration was produced for Malawi and Kenya by the Malawi and Kenya National Met services. This information was not available in Tanzania because the appropriate sensors did not exist for the met stations being studied. For these sites we used the NOAA NCEP-NCAR CDAS-1 monthly diagnostic surface potential evaporation climatology evaporation data, measured in watts/ m^2, to run the crop loss financing model. This is a global gridded dataset available through sources such as the IRI data library. Following (Ebisuzaki 2006) we converted the watts per m^2 evaporation data of the NOAA NCEP-NCAR CDAS-1 data into mm/day by multiplying the reported latent heat flux (W/m^2) by 0.03456, a conversion factor determined by the following equation:

1 W/m/m * (1 / Latent heat at OC) * (1/ density of water) * (seconds / day) * (mm/m) *1 (J/m/m/s) * (1/2.5e6 kg/J) (1/1e3 m*m*m/kg) * (24*60* 60 second / day) * (1000 mm/m)

= 0.03456 mm/day

This conversion assumes that both the density of water and the latent heat of evaporation are constant (Ebisuzaki 2006).

To download, go to: http://iridl.ldeo.columbia.edu/expert

And paste this in, with the desired lat/lon in the x, y below. Final data can be downloaded from the data library:

SOURCES .NOAA .NCEP-NCAR .CDAS-1 .MONTHLY .Diagnostic .surface .potential .evap

T (Jan 1960) (last) RANGE X (35.6) VALUE Y (-3.9) VALUE yearly-climatology

APPENDIX V. DSSAT MODEL BACKGROUND

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software that uses crop, soil, and weather databases in combination with crop models to simulate outcomes of crop management strategies. The DSSAT crop models are more detailed crop models than the WRSI equation, as they simulate the biological processes in the plant, as opposed to simply performing water balance accounting. They include more variables than water availability in their estimates of crop yields. DSSAT consists of eight modules: a Land Module; Management Module; a Soil Module made up of two soil nitrogen and organic matter modules and a soil water balance sub-module; a Weather Module capable of reading or generating daily weather data; a Soil-Plant-Atmosphere Module that accounts for the competition for light and water between the soil, plants, and the atmosphere; the CROPGRO Plant Growth Module which simulates the growth of grain legumes, vegetables, and grasses; the CERES Plant Growth Module which simulates growing grain cereals; and the SUBSTOR Plant Growth Module, used to simulate potato growth.

Ideally extensive calibration and verification against observed crop growth in a controlled setting is performed prior to use of the system in predicting plant behavior. In order to calibrate and run the crop models an array of data is required, with simulation results sensitive to parameter assumptions. Weather data for the duration of the growing season and preferably beginning a few weeks prior to planting and extending a few weeks after harvest is needed. This includes daily values of incoming solar radiation, maximum and minimum air temperatures, and daily rainfall. Optional data includes dry and wet bulb temperatures and wind speed.

Soil data is required, including soil classification, surface slope, color, permeability, drainage class, soil profile data by soil horizon. The soil profile data consists of upper and lower horizon drainage depths, percentage sand silt and clay content, 1/3 bar bulk density, organic carbon, pH in water, aluminum saturation, and root abundance information. Finally, management and experiment data is required, including planting date, planting density, row spacing, planting depth, crop variety, irrigation, and fertilizer practices.

APPENDIX VI. Data requirements

Minimal data requirements to run prototype contract generation software consists of the following information:

Historical daily rainfall amounts at each station.

The most convenient format for us is a comma separated file for each station using the format below. Leap day is left blank for non leap years.

Climatological ET over the growing season (average potential et for each time period during the growing season, dekadal time periods are acceptable). If there are complexities in the provision of this, it would be worthwhile to have a dialog with the provider over the best methods of generation and what types of data is available to use for generating ET.

Table 7.1 Format for daily rainfall data to run prototype contract generation software.

	1961	1962	1963	1964	1965	1966	1967
I-Jan	11.4	6.6	21.8	0	20.6	0	0
2-Jan	1.5	27.2	29	3	15	0.5	0

Phenology for each station and crop, and variety

This would include the start of the growing season, the approximate time of flowering, and the length of the growing season. If locally adjusted Kc and Ky coefficients are available for the WRSI model, those would be useful. If time from sowing to germination is available, that would be of use as well.

Sowing window and sowing rules

In Malawi, the sowing rule was a minimum amount of rainfall per dekad in the sowing window. Each contract would require a sowing rule.

Water holding capacity (WHC, in mm per m) at each station

If there is a soil depth or similar constraint on water storage, this information would also be necessary.

Values to assume for: Soil Water Content Fraction, Maximum Crop Root Depth (m), Effective Crop Root Depth

The parameters are described in Term Sheet Example: Malawi Transaction Appendix 1. The parameters presented in that document will be used if local parameters are not available.

Costs of inputs and price per kg of yields (optional if not building bundled loan package)

Approximate yield levels without water stress (optional if not building bundled loan package)

Contracts can be developed without the data below, but their availability allows much greater quality contracts to be developed. Historical harvest data Station location, elevation Typical practices, inputs used

APPENDIX VII. COOPERATIVE DESIGN QUESTIONNAIRE

The following example is from the INITIAL QUESTIONS FOR FIELD WORK IN KENYA 13-2-07 (Bryla 2007)

Discussion of clients' risks, income generating activities, access to finance, and production approaches

Income

- What are your main sources of income?
- How much of your income comes from the production and sale of maize?
- How much of your maize do you sell vs. consume?
- What are your main sales markets? Who do you sell your maize to?
- On average what are the prices you receive for you maize? Recent years high vs. low.
- Do you do any forward contracting for the maize?

Risk

- What are your biggest risks to your income? Weather, price, etc
- How do you currently manage risk?
- What are the specific weather risks that maize production faces?
- Drought When during the season?
- Excess Rain If ever, when during the season?
- Temperature If ever, when during the season?

Access to Finance

- Do you receive financing for this production?
- From who?
- What type of financing? What are the terms?
- Are you interested in accessing additional financing for production?
- What time of year is the financing received?
- What types of collateral do you normally provide?

Production

• What type of maize do you plant? Hybrid, opv, local?

- What type of fertilizers or inputs do you use? When are they applied during the season? What are the costs of these inputs?
- What is the typical planting period for maize?
- What is the earliest date that you have planted and what year was that in?
- What is the latest date you have planted, and what year was that in?
- When does your hybrid maize typically tassle and fill?
- When do you typically harvest?

Detailed explanation of the product - talking points rather then questions

- Product is based on an index where a rainfall index acts as proxy for yield rather then measuring yield itself
- Farmers must be somewhat confident the rainfall on their farm is similar to rainfall at the weather station
- Basis risk is present and could affect the effectiveness of the contract
- Insure premiums require an upfront cash payment and are non refundable
- Index insurance only covers the named peril for which it was designed and other risks could cause yield losses for which the farmer will not be covered
- Product is commercially based and not subsidized

Discussion of the contract parameters

- What are the best years and the worst years for maize production that you can remember?
- What made these years the best and worst years? What were the specific events that caused yield to be good or bad?
- Does the dynamic sowing period reflect your sowing practices? Ie do you wait for the first rains to sow?
- How do you judge when rain is sufficient for planting?
- What do you do if rains are insufficient for planting? Plant a different crop vs plant anyway etc?
- Is sowing and tasseling the two times when you feel that they are most vulnerable to drought?
- If there is a different part of the growing season in which your crops have been vulnerable to drought, what is this part, what month(s) does it occur, and in what years has it been a problem?
- In which years did you have yield problems because of drought, and for each year, what was the reason for the problem (eg dry sowing/weak start of rains or drought during the filling phase)?
- Do the historical payouts match the years in which you would have expected a payout?

Discussion of Willingness to pay

- Would you be willing to pay for the insurance product that was described above?
- How much would you be willing to pay? In absolute terms and percentage basis.
- Would you be willing to pay if you could get a loan for the cost of the premium?
- Would you be willing to pay if this would give you access to a loan for inputs?
- If not from loans where would you get the cash to pay for the premium?

APPENDIX VIII. INITIAL EXPLORATIONS OF FAILED SOWING

We performed exploratory analysis into alternative techniques that might be applicable for insuring failed sowing events. Although we did not implement changes in the contracts based on this analysis, it is possible that a simple rule based on the number of days when WRSI equaled zero during the first week of sowing may be effective. An example illustration of this criterion is below. The results of this are shown for Lilongwe in Figure A8.1. We then compared the number of years when WRSI equaled zero for different time-spans within the first week after sowing, as shown in Figure A8.2. It is possible that dry spell measure based on strings of days with WRSI of zero may be a worthwhile index to pursue for failed sowing or crop failure if the methods currently used are not sufficiently effective for a particular application.



Figure A8.1 Days within the first week after sowing where WRSI=0 for the Lilongwe maize crop.


Figure A8.2 Number of years where WRSI=0 in the first week after sowing for the Lilongwe maize crop.

APPENDIX IX. ADDITIONAL SIMULATIONS

Table A9.1 Statistical Comparison for DSSAT crop yield and decadal and daily WRSI based crop yield using average Ky and 4stage Ky values for Lilongwe groundnut crop.

	0 0 1				
	DSSAT Crop Yield	Dekadal CPI (av Ky)	Dekadal CPI (4 Kys)	Daily CPI (av Ky)	Daily CPI (4 Kys)
Min	700	710	799	670	762
Max	6266	1000	998	970	990
Average	4381	890	927	811	871
STDEV	1241	64.6	49.3	66.2	53.0
CV	0.28	0.07	0.05	0.08	0.06

Figure A9.1 Lilongwe groundnut crop yields as estimated using dekadal and daily WRSI with average and 4-stage Ky values, and the DSSAT crop model



	DSSAT Crop Yield	Dekadal CPI (av Ky)	Dekadal CPI (4 Ky)	Daily CPI (av Ky)	Daily CPI (4 Ky)
Min	447	500	594	450	581
Max	6248	1000	999	950	977
Average	3670	870	912	796	861
STDEV	1766	96.3	77.4	85.0	70.8
CV	0.48	0.11	0.08	0.11	0.08

Table A9.2 Statistical comparison of decadal and daily WRSI based crop yields using average Ky and 4-stage Ky values and the DSSAT crop model for Kasungu groundnut crop.

Figure A9.2 Kasungu groundnut crop yields as estimated using dekadal and daily WRSI with average and 4-stage Ky values, and DSSAT crop model.



	Dekadal CPI (av Ky)	Dekadal CPI (4 Ky)	Daily CPI (av Ky)	Daily CPI (4 Ky)
2553	770	793	740	766
6559	1000	1000	1000	1000
4931	959	968	891	920
933	55.3	47.4	60.6	50.4
0.198	0.06	0.05	0.07	0.05
	6559 4931 933	65591000493195993355.3	655910001000493195996893355.347.4	6559100010001000493195996889193355.347.460.6

Table A9.3 Statistical comparison of decadal and daily WRSI based crop yields using average Ky and 4-stage Ky values and the DSSAT crop model for Kasungu groundnut crop.

Figure A9.3 Nkhotakota groundnut crop yields as estimated using dekadal and daily WRSI with average and 4-stage Ky vales, and DSSAT crop model.





Figure 9.4 Lilongwe maize yields as estimated using daily and dekadal WRSI with average and 4-stage Ky values, and DSSAT crop model.

Figure 9.5 Nkhotakota maize crop yields as estimated using daily and dekadal WRSI with average and 4-stage Ky values, and DSSAT crop model.





Figure 9.6 Kasungu maize crop yields estimated from Dekadal and Daily WRSI using average Ky and 4-stage Ky values, and the DSSAT crop model.

Figure 9.7. Chitedze maize crop yield estimates from dekadal and daily WRSI using average and 4-stage Ky values and the DSSAT crop model.



APPENDIX X. CONTRACT COMMUNICATION TOOL







































BIBLIOGRAPHY

International Institute for Applied Systems Analysis (2006). Concept Testing for Weather Based Insurance report to World Bank CRMG prepared by Beth Mwangi, Market Research Consultant.

Bryla, E. C., World Bank (2007). Initial Questions for Field Work in Kenya 13-2-07. D. Osgood. Personal Correspondence 14 February

Chavula, A. a. R. G. (2006). Development of a Weather Yield Index (WYX) for maize Crop Insurance in Malawi, Food and Agriculture Organization of the United Nations.

Commodity Risk Management Group, World Bank (2006). Terms of Reference for IRI, Earth Institute, Columbia University: Designing Weather Insurance Contracts for Farmers in Malawi, Tanzania, and Kenya.

Ebisuzaki, W. (2006). D. Osgood. Personal Correspondence. 01 November

Hull, J. C. (1998). Futures and Options Markets. Upper Saddle River, New Jersey, Prentice Hall.

International Institute for Applied Systems Analysis (2007). The Feasibility of Risk Financing Schemes for Climate Adaptation: The Case of Malawi research report to the DEC-Research Group, Infrastructure and Environment Unit of the World Bank prepared by Suarez, Pablo, J. Linnerooth-Bayer, Reinhard Mechler, International Institute for Applied Systems Analysis (IIASA).

Malawi Department of Meteorological Services. (2007). "Climate." Malawi Meteorological Services, from http://www.metmalawi.com/climate/climate.php.

Malawi Department of Meteorological Services (2007). First Round 2006/2007 Agricultural Estimates Agrometeorological Update.

Munthali, G. K. e. a. (2003). Drought case Study for Malawi. Dealing with Extreme Climatic Events. Chileka, Malawi Department of Meteorological Services.

Nelder, J. A. a. M., R. (1965). "A Simplex Algorithm for Function Minimization." Computer Journal 7.

Skees, J., P Hazell, and M. Miranda (1999). New Approaches to Crop Yield Insurance in Developing Countries International Food and Policy Research Institute, Environment and Production Technology Division.

Commodity Risk Management Group, (2005). Designing the Weather Insurance Structure for Malawi, CRMG, World Bank.

Commodity Risk Management Group, (2006). Weather Risk Management for Agriculture Risk Management in Agriculture for Natural Hazards, ISMEA.

Technoserve, T. (2006). Developing a Weather Risk Management Pilot Program in Tanzania Report to World Bank CRMG prepared by Nargis Suleman and Paul Stewart, Technoserve, Tanzania.