Catastrophic Drought Insurance based on the Remotely Sensed Normalized Difference Vegetation Index for Smallholder Farmers in Zimbabwe

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Abstract

Index insurance, which indemnifies agricultural producers based on an objectively observable variable that is highly correlated with production losses but which cannot be influenced by the producer, can provide adequate protection against catastrophic droughts without suffering from the moral hazard and adverse selection problems that typically cause conventional agricultural insurance programs to fail. Using historical maize and cotton yield data from nine districts in Zimbabwe, we find that catastrophic drought insurance contracts based on the Normalized Difference Vegetation Index (NDVI) can be constructed whose indemnities exhibit higher correlations with yield losses compared to the conventional rainfall index. In addition the NDVI contracts can be offered within the 5–10 per cent premium range considered reasonably affordable to many poor smallholder farmers in Zimbabwe.

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1. BACKGROUND AND MOTIVATION

More than 60 per cent of Zimbabwe's population consists of smallholder farmers who practice rain-fed subsistence and semi-subsistence agriculture that is vulnerable to severe, often life-threatening droughts. Like most countries in Southern Africa, Zimbabwe historically has responded to severe droughts by implementing ad hoc emergency food aid programs. These government-administered programs, however, historically have been riddled with a variety of problems. First, the costs of these programs have often been exorbitant, sometimes reaching 10 per cent of the annual GDP after an extreme drought (Heal & Lin, 1998). Second, these programs have been vulnerable to political abuse, often leading to inequitable distribution of benefits. And third, due to mismanagement and the absence of an adequate distribution infrastructure, these programs have often suffered large-scale logistical failures.

Perhaps the most severe criticism that may be leveled at ad hoc emergency food aid programs in developing countries, however, is that they nurture a culture of dependency that discourages recipients from implementing effective household-level risk mitigation and risk management strategies. While food aid partly addresses the problem of transitory household food insecurity, it does not provide a permanent solution to household food insecurity and chronic poverty. In Drebe and Sen's words (1982:67), food aid "*conjures up the picture of a battle already half lost and focuses the attention on emergency operations narrowly aimed at containing large-scale mortality*".

Access to affordable private or government agricultural insurance could substantially reduce the vulnerability of smallholder farmers to drought risk and promote efficient uses of scarce resources, while diminishing smallholder dependence on expensive and often ineffective food aid measures. The benefits of agricultural insurance are well known. Agricultural insurance can stabilize farmers' incomes and protect them from the impacts of catastrophic crop failures; it can encourage farmers to adopt technologies that increase production; and it can reduce loan default risk, allowing farmers to secure more favorable credit terms (Binswanger, 1986).

Agricultural insurance, however, is unavailable in Zimbabwe and, more generally, in Southern Africa. The absence of agricultural insurance may be attributable to the widespread belief that poor smallholders lack the sophistication to properly use insurance to manage risk (Zeller & Sharma, 2000; Zeller, 2003). However, agricultural insurance, particularly traditional multi-peril crop insurance (MPCI), suffers from more fundamental problems that have caused it to fail in many developing countries (Hazell et al., 1986; Miranda, 1991; Roberts & Dick, 1991; Gudger, 1991; Hazell 2006). Traditional MPCI is vulnerable to asymmetric information problems, such as moral hazard and adverse selection, which undermine the actuarial soundness of the insurance product. Moral hazard arises when the insured, after obtaining insurance, alters production practices so as to increase the likelihood of receiving an indemnity; adverse selection arises when the insured is better informed of his chances for losses than the insurer, resulting in a self-selected pool of insured farmers who, on average, receive indemnities that exceed premiums paid. Traditional MPCI is also expensive to administer because it requires

individual farm-level rate-setting, monitoring, and loss adjustment. As concluded by Binswanger (1986), the cost of traditional crop insurance, not the lack of demand or managerial sophistication among farmers, has been the greatest obstacle to the development of agricultural insurance markets.

In response to the inherent limitations of traditional MPCI, agricultural economists and policy makers have developed a growing interest in alternative agricultural insurance designs. These alternative designs take the form of "index" insurance contracts, which indemnify farmers based on an objectively observable variable, or index, that is highly correlated with farm-level losses, but which cannot be influenced by the actions of the insured. A variety of indices have been used or suggested in recent years in agricultural insurance designs, including area yields, rainfall, heat-stress indices, and El Niño – Southern Oscillation indices (Vedenov & Miranda, 2001; Khalil et al 2007; Skees, 2008;).

Index insurance possesses a number of attractive features. First, since farmers cannot influence the value of the index, index insurance is effectively free of moral hazard. Second, because indemnities are based on generally observed variables, it is relatively free of adverse selection problems. Third, since index insurance does not require on-farm inspections and field loss assessments, it is relatively inexpensive to administer. However, index insurance has some potential limitations. Most notably, it only covers losses directly associated with the index, say, widespread drought, while leaving the farmer exposed to other idiosyncratic losses such as fire. Ultimately, the viability of any index

insurance contract depends on correlation between the indemnities provided by the contract and the farmer's production losses.

In this paper, we explore the feasibility of offering index insurance contracts to Zimbabwe smallholders that are based on two distinct indices: rainfall measurements taken at established meteorological stations, and remotely-sensed Normalized Difference Vegetation Index (NDVI) measurements provided by orbiting National Oceanic and Atmospheric Administration (NOAA) satellites.[2] Both indices meet, prima facie, the most important necessary conditions for use as an insurance index: they are objectively and reliably measureable and are not subject to manipulation by either the insurer or the insured. To be determined is whether a specific contract design can be found that meets all the other conditions for economic viability as an insurance contract (Skees et al., 1999). These conditions include the following: (i) the contract must be affordable and accessible to the majority of the farmers, including poor smallholders in Zimbabwe; (ii) the contract should compensate for catastrophic income losses and protect subsistence consumption; (iii) the contract ought to be provided either by the private sector or public sector with few or no government subsidies; and (iv) there should be sufficient data to allow the contract to be actuarially rated with few opportunities for adverse selection problems to arise.

[2] Drought insurance was first proposed in India in 1920 by Chakravarti, who observed that "*no insurance authority … would be able to watch and enforce that every insured field receives the required amount of care and attention at the hands of its cultivator. Unless some method can be devised by which this great difficulty is eliminated, a system of crop insurance would indeed be impossible.*" He added that given the dependence of Indian agriculture on rainfall, drought insurance "*is not only possible but also practicable*" (Mishra 1996: 309).

2. INNOVATIONS IN REMOTE SENSING TECHNOLOGY

Recent advances in satellite remote sensing technology now permit accurate measurements at particular spatial scales and spectral bandwidths that allow dynamic monitoring of environmental conditions such as vegetation cover. Remote sensing has proven a powerful tool for evaluating crop growing conditions and drought (Johnson et al., 1993; Peters et al., 2002). In recent years, many organizations and national governments have shown growing interest in using satellite data for drought early warning and crop yield assessment (Johnson et al., 1993).

Remotely sensed data produced by the Advanced Very High Resolution Radiometer (AVHRR) sensor aboard the NOAA series of polar-orbiting satellites of the USA are extensively used for drought early warning and food security purposes (Johnson et al., 1993; Kogan, 1998). NOAA-AVHRR satellites provide twice-daily coverage of the planet's surface, making them ideal for early warning systems, drought monitoring, crop assessment and yield estimation. Another advantage with NOAA-AVHRR satellites is that, given their daily coverage, they are likely to provide more cloud-free images compared to other satellites, such as LANDSAT. Further, data produced by NOAA-AVHRR satellites are accessible at many receiving stations around the world in near-real time. However, the disadvantages of NOAA-AVHRR data pertain to their low spatial resolution and their vulnerability to geometric and radiometric distortions.

Today, several remotely sensed indices based on satellite measurements, including the NDVI developed by Kogan (1998), are used widely to measure vegetation stress and

assess crop yields. The NDVI is a plausible choice of index for an agricultural insurance contract because it is highly correlated with crop yields, easy to measure on a regular basis, and not subject to manipulation by agricultural producers or insurers. NDVI sequential crop profiles show the progression of canopy emergence, maturation and senescence during the growing season, allowing crop yields to be assessed and/or predicted with considerable accuracy. The NDVI is an indicator of the vigor of vegetation, which is a consistent index across different types of land cover (Vogt et al., 2000). The NDVI, furthermore, is designed to separate short-term from long-term weather signals as reflected by typical vegetation cover, making it a good indicator of water stress conditions (Kogan & Sullivan, 1993; McVicar & Jupp, 1998).

3. DATA

In our analysis, we examine the economic viability of drought index insurance contracts based on each of two indices, rainfall and the NDVI, for nine districts in Zimbabwe – Chiweshe, Gutu, Sanyati, Chivi, Mt Darwin, Wedza, Hurungwe, Shamva and Beitbridge. These districts are located in different agro-ecological natural regions classified as II–V[3] with markedly different soil fertility, rainfall patterns, crop practices and management. For both indices and all nine regions, we seek to find an index insurance design that provides adequate coverage against losses experienced by maize and cotton producers. To perform our analysis, rainfall, NDVI and maize and cotton yield data were obtained from various sources.

[3] Zimbabwe's agricultural land is sub-divided into five agro-ecological natural regions numbered I to V. Agricultural potential declines from region I to region V.

Historical annual maize and cotton production data for nine districts in Zimbabwe were obtained from the department of Agricultural Research and Extension Services (AGRITEX) for the period 1980 to 2001.[4] Maize, the main staple in these nine districts (Table 1), is grown by over 80 per cent of smallholders and accounts for more than 60 per cent of cultivated land. Cotton, the main cash crop, accounts for about 18 per cent of cultivated land. Complete time series of maize yields were available for all nine districts of interest; however, complete time series of cotton yields were available only for the Chiweshe, Sanyati, Hurungwe and Shamva districts. Both crops are grown largely under rain-fed conditions in these regions.

Table 1: Average maize and cotton yield by nine selected districts, Zimbabwe, 1980-2001

District	Natural region	Maize		Cotton	
		Production (MT)	Yield (MT/acre)	Production (MT)	Yield (MT/acre)
Chiweshe	II	27,336	2.285	1,035	0.808
Gutu	III	11,192	0.564	817	0.411
Sanyati	IV	6,189	1.067	5,432	0.798
Chivi	V	15,996	0.555	578	0.548
Mt Darwin	IV	4,729	0.920	917	0.659
Wedza	III	15,059	1.064	275	0.544
Hurungwe	II	104,686	1.859	14,701	0.815
Shamva	II	25,190	1.439	611	0.683
Beitbridge	V	1,221	0.135	–	–

[4] The period 2002–2008 was deliberately avoided, since it coincided with Zimbabwe's land reform program which was often marked by violence and chaos.

NOAA-AVHRR NDVI data for the period 1980–2000 were obtained from the Southern African Development Community (SADC) Regional Remote Sensing Unit based in Gaborone, Botswana. The data are received at decadal (10-day) intervals and geo-referenced to the nine selected districts. Monthly rainfall data were obtained for the period 1980–2000 from the Zimbabwe Department of Meteorology. The data are aggregated by the number of weather stations within each of the nine selected districts. A drawback with this approach is that the data are obtained from a sparsely distributed network of weather stations and often fail to capture the spatial distribution of crop losses. In contrast, satellite-derived variables like NDVI come with the relatively high spatial and temporal resolution essential for continuous monitoring of crops during the growing season and for crop loss assessment. These satellite variables, however, have their own downside as they may be difficult to interpret over heterogeneous terrain. Further, the use of any index by virtue of being surrogate for insurance losses involves basis risk.[5]

Table 2 provides a summary of descriptive statistics pertaining to NDVI and rainfall data for the nine selected districts during the growing season that runs from January to April. For districts located in the driest regions (NR V) such as Beitbridge and Chivi, NDVI values range from 0.33 to 0.60, while for the wettest districts such as Hurungwe and Chiweshe (NR II), recorded NDVI values are slightly higher (0.45–0.64). Within semi-arid regions (NR III and IV), NDVI values vary from 0.38 to 0.58 and 0.38 to 0.66 respectively. Further, NDVI values are generally low during the early part of the season

since most crops are still at early stages of growth. But as the season progresses and crops attain full maturation the NDVI peaks, reaching its maximum (0.66) by the month of February. Using standard deviation as a measure, we tend to observe higher variability in NDVI values during the January–March period affecting the driest districts as opposed to the wettest districts. This marked variation in NDVI values is a crucial factor in accounting for observed yield variation across regions.

Rainfall, on the other hand, is received mostly during the month of January, with the wettest districts receiving on average 250 mm, compared to 95 mm in drier districts. Thus for both indices the period January–February is the most crucial yield-determining phase for most crops. However, as the season nears its end (around March/April), rainfall decreases, crop senescence sets in and NDVI values decline correspondingly.

[5] Basis risk refers to the risk of not paying indemnities when the insured suffers compensatory losses and vice versa.

Table 2: Descriptive statistics for NDVI and rainfall data by district, 1980–2000

	Natural		NDVI				Rainfall (mm)			
District	region	Statistic	Jan	Feb	Mar	Apr	Jan	Feb	Mar	Apr
Chiweshe	II	Min	0.48	0.48	0.52	0.45	63	32	10	0
		Max	0.60	0.63	0.62	0.58	479	351	255	91
		Mean	0.56	0.60	0.59	0.53	228	220	120	25
		Stdev	0.03	0.04	0.03	0.03	106	106	78	26
Gutu	III	Min	0.41	0.42	0.45	0.41	23	0	4	0
		Max	0.55	0.55	0.53	0.52	320	341	120	94
		Mean	0.47	0.50	0.49	0.47	132	110	57	18
		Stdev	0.03	0.03	0.03	0.03	93	94	42	24
Sanyati	IV	Min	0.49	0.50	0.53	0.46	50	4	10	0
		Max	0.66	0.66	0.65	0.62	387	365	204	96
		Mean	0.60	0.62	0.61	0.56	199	134	85	22
		Stdev	0.04	0.04	0.04	0.04	101	102	63	28
Chivi	V	Min	0.42	0.43	0.44	0.41	23	0	4	0
		Max	0.60	0.58	0.61	0.56	320	341	120	94
		Mean	0.51	0.53	0.53	0.50	132	110	57	18
		Stdev	0.04	0.05	0.05	0.04	93	94	42	24
Mt Darwin	IV	Min	0.50	0.49	0.48	0.45	37	13	1	0
		Max	0.59	0.62	0.61	0.59	453	395	287	99
		Mean	0.54	0.58	0.58	0.53	213	203	91	20
		Stdev	0.03	0.03	0.03	0.03	101	114	86	34
Wedza	III	Min	0.45	0.47	0.49	0.42	27	7	13	0
		Max	0.58	0.58	0.56	0.54	416	375	205	155
		Mean	0.51	0.54	0.53	0.50	203	153	86	33
		Stdev	0.03	0.03	0.02	0.03	108	102	57	40
Hurungwe	II	Min	0.47	0.50	0.52	0.48	68	61	29	0
		Max	0.64	0.65	0.64	0.63	366	428	229	168
		Mean	0.59	0.62	0.60	0.55	194	195	109	33
		Stdev	0.04	0.04	0.03	0.04	85	91	58	42
Shamva	II	Min	0.49	0.51	0.49	0.49	79	0	22	0
		Max	0.59	0.62	0.62	0.60	433	296	237	119
		Mean	0.55	0.58	0.58	0.54	231	180	104	31
		Stdev	0.03	0.03	0.03	0.03	95	91	68	35
Beitbridge	V	Min	0.37	0.38	0.38	0.37	0	2	4	0
		Max	0.62	0.58	0.60	0.55	294	394	120	119
		Mean	0.48	0.49	0.48	0.46	69	68	32	12
		Stdev	0.07	0.06	0.06	0.05	69	93	29	27

Table 3 shows the correlation of maize and cotton yields with monthly total rainfall and monthly average NDVI values during the critical crop growth period of January to April. As seen in Table 3, the correlation between maize yields and the NDVI is lower during the early part of the season but improves dramatically as the season progresses and attains a maximum predominantly during the month of March; for cotton the highest correlation with the NDVI is attained during the month of April. The highest correlations between rainfall and maize yields are attained predominantly during the month of February, whereas the highest correlations between rainfall and cotton yields alternate between January and February across districts. The temporal patterns of correlations are sensible, as they tend to show low correlation at the beginning and end of the season. Given that both crops are still in the early stages of growth around January, one would generally expect weak correlations. However as the season progresses, the correlations between both indices and yields improve dramatically, especially for the period February–March which generally corresponds to flowering and grain-filling stages for most crops. Towards the end of the season (April), most crops would have attained full maturation, with senescence setting in, generally marked by diminishing greenness and vigor, resulting in a decline in correlation.

Table 3: Correlation between yields and NDVI and rainfall, by crop, region and month

	NDVI					Rainfall			
	Jan	Feb	Mar	Apr		Jan	Feb	Mar	Apr
Maize									
Chiweshe	0.10	0.12	0.26	0.21		0.14	0.60	0.51	-0.22
Gutu	0.52	0.49	0.40	0.28		0.19	0.57	0.06	0.00
Sanyati	-0.11	0.12	0.29	0.14		0.32	0.64	-0.12	0.25
Chivi	0.49	0.65	0.71	0.63		0.40	0.46	0.21	-0.14
Mt Darwin	-0.32	-0.11	0.36	0.48		-0.10	0.21	0.50	-0.18
Wedza	0.29	0.36	0.39	0.14		0.51	0.35	-0.14	0.09
Hurungwe	0.21	0.37	0.44	0.31		0.34	0.35	-0.05	0.19
Shamva	0.11	0.11	0.29	0.19		0.41	0.51	0.31	0.18
Beitbridge	0.28	0.33	0.39	0.41		0.31	0.40	0.02	-0.07
Cotton									
Chiweshe	-0.30	-0.43	-0.21	-0.16		0.41	0.61	0.19	-0.09
Sanyati	-0.01	0.19	0.48	0.55		0.36	0.33	0.30	0.11
Hurungwe	0.00	0.17	0.47	0.61		0.47	0.25	0.26	0.02
Shamva	0.18	0.02	0.20	0.17		0.44	0.49	0.48	0.14

4. **Insurance contract design and specification**

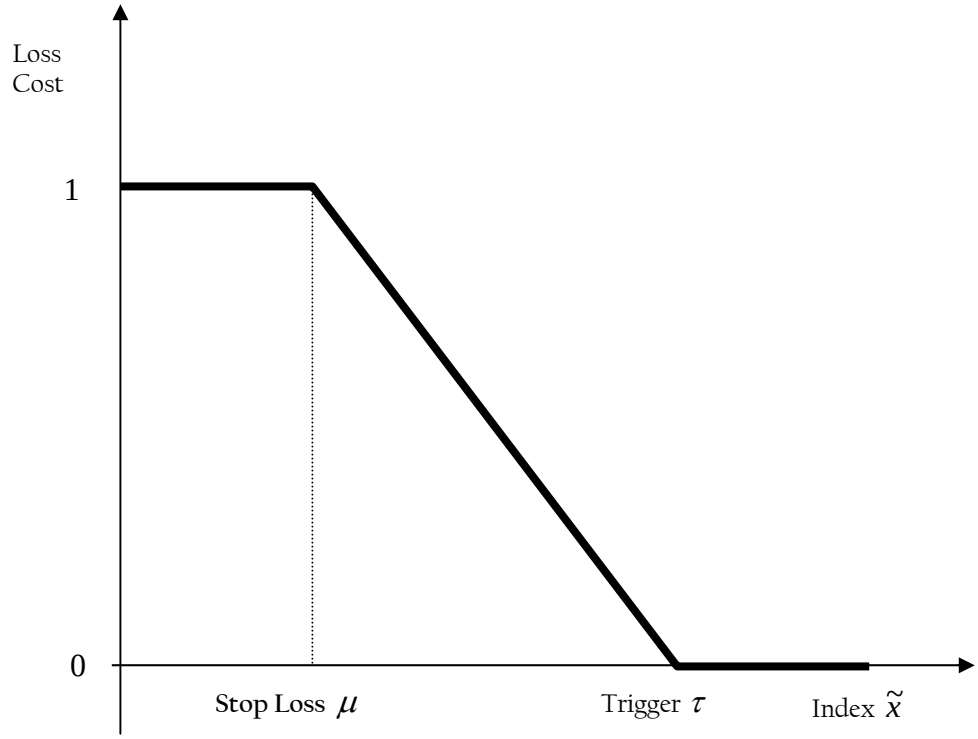
We envisage a simple proportional insurance contract with a stop-loss provision. The indemnity schedule associated with such a contract, which is illustrated in Figure 1, takes the form

$$f(\tilde{x};\tau,\mu)=\begin{cases}1 & \text{if } \tilde{x}<\mu \\ \dfrac{(\tau-\tilde{x})}{(\tau-\mu)} & \text{if } \mu\le\tilde{x}\le\tau \\ 0 & \text{if } \tilde{x}>\tau\end{cases}$$

Here $f(\tilde{x};\tau,\mu)$ denotes the indemnity paid per dollar of liability, or "loss cost", conditional on realization of the prescribed index $\tilde{x}$, for specified values of a "trigger" τ and "stop-loss" μ. As seen in Figure 1, the contract pays nothing if the index $\tilde{x}$ exceeds the trigger τ, pays full indemnity if the index $\tilde{x}$ falls below the stop-loss μ, and pays a

proportional indemnity whenever the index $\tilde{x}$ lies between the trigger τ and the stop-loss μ.

Figure 1: Indemnity schedule for a Standard Unit Index insurance contract



Our method of selecting and pricing an index insurance contract is based on the approach taken by Vedenov & Miranda (2001). In particular, we search among the critical growing season months of January, February, March and April for values of the trigger τ and stop-loss μ that maximize the correlation between losses of interest and indemnities, while requiring the expected loss cost, also known as the "fair premium rate", to equal an affordable level, in this case either 5 per cent or 10 per cent. We define a loss to be any deficit in production below 85 per cent of historically average production.

More formally, for each of the nine districts, two crops, two indices, and four growing season months, we solved

$$\begin{array}{ll} \underset{\tau,\mu}{Max} & Corr(f(\tilde{x};\tau,\mu), Max(\theta\bar{y}-\tilde{y},0)) \\ \hline s.t. & E\ f(\tilde{x};\tau,\mu)=\pi \end{array}$$

for the optimal trigger τ and stop-loss μ. Here, $Corr$ is the correlation operator, E is the expectation operator, $\tilde{x}$ are the historically observed index values, $\tilde{y}$ are the historically observed district-level yields, $\bar{y}$ is the historical mean of the district-level yields, $\theta = 0.85$ is the percentage of the historical mean at which losses begin to be measured, and π, which equals 0.05 or 0.10, is the target fair premium rate. The optimum was computed by performing a refined grid search on the trigger τ, with the corresponding stop-loss μ computed numerically from the target fair premium rate constraint using the secant method (Miranda & Fackler, 2002).

4.2 Results

Of practical importance is the optimal period to offer or write contract insurance based on either NDVI or rainfall index. For each crop and region, we searched across the growing season months of January, February, March and April to find which months would provide the maximum loss-indemnity correlation. The results are presented in Tables 4(a) and 4(b).

As shown in Table 4(a), across most districts the optimal period for offering maize NDVI contracts tended to be the months of February and March. The optimal months were robust to the specification of the target premium rate. In addition, across most districts the

NDVI exhibits appreciably high correlations with maize yield losses in the range 0.40–0.90. The optimal months to offer NDVI cotton contracts ranged from February to April, with loss-indemnity correlations in the range 0.40–0.52.

As seen in Table 4(b), the month of February is optimal for offering maize rainfall insurance contracts across most districts. For two districts (Hurungwe and Shamva) however, the month of January is the optimal month. The results are robust at 5–10 per cent premium rates. With respect to cotton, the reverse is true; for a 5 per cent premium rate, the month of January was predominantly optimal; whereas for a 10 per cent premium rate the months January and February were optimal.

Table 4(a): NDVI insurance: optimal month, stop point, trigger point, and loss-indemnity correlation by crop, region, and premium rate

	--- Premium rate = 5% ---				--- Premium rate = 10% ---			
	Month	Stop	Trigger	Correl.	Month	Stop	Trigger	Correl.
Maize								
Beitbridge	Feb	0.21	0.44	0.50	Feb	0.33	0.44	0.50
Chivi	Mar	0.33	0.49	0.87	Mar	0.41	0.49	0.87
Chiweshe	Mar	0.49	0.55	0.45	Feb	0.54	0.55	0.45
Gutu	Feb	0.37	0.47	0.84	Feb	0.45	0.45	0.88
Hurungwe	Mar	0.20	0.62	0.40	Mar	0.41	0.62	0.40
Mt Darwin	Mar	0.08	0.60	0.86	Mar	0.34	0.60	0.86
Sanyati	Mar	0.23	0.61	0.54	Mar	0.42	0.61	0.54
Shamva	Feb	0.51	0.51	0.52	Feb	0.52	0.53	0.52
Wedza	Mar	0.16	0.55	0.56	Mar	0.35	0.55	0.56
Cotton								
Chiweshe	Mar	0.51	0.53	0.39	Feb	0.54	0.55	0.39
Hurungwe	Apr	0.01	0.57	0.45	Apr	0.12	0.60	0.47
Sanyati	Apr	0.10	0.58	0.52	Apr	0.34	0.58	0.52
Shamva	Feb	0.50	0.52	0.42	Feb	0.52	0.53	0.42

Table 4(b): Rainfall insurance: optimal month, stop point, trigger point, and loss-indemnity correlation by crop, region, and premium rate

	--- Premium rate = 5% ---				--- Premium rate = 10% ---			
	Month	Stop	Trigger	Correl.	Month	Stop	Trigger	Correl.
Maize								
Beitbridge	Feb	0	9	0.22	Feb	1	15	0.43
Chivi	Feb	0	2	0.56	Feb	5	9	0.45
Chiweshe	Feb	47	47	0.73	Feb	75	77	0.73
Gutu	Feb	0	2	0.52	Feb	3	11	0.38
Hurungwe	Jan	57	72	0.48	Jan	67	91	0.44
Mt Darwin	Feb	1	34	0.50	Feb	1	84	0.66
Sanyati	Feb	1	11	0.61	Feb	14	17	0.70
Shamva	Jan	2	137	0.50	Jan	28	168	0.57
Wedza	Feb	12	13	0.62	Feb	23	32	0.67
Cotton								
Chiweshe	Mar	13	14	0.73	Feb	14	127	0.83
Hurungwe	Jan	60	70	0.85	Jan	67	91	0.68
Sanyati	Jan	0	99	0.25	Feb	14	17	0.64
Shamva	Jan	2	137	0.37	Jan	14	176	0.45

We further extend our analysis by invoking the concept of the mid-season dry spell risk factor. During any growing season, the mid-season dry spell coincides with the critical crop growth period (which encompasses the tassel and grain-filling stages) that influences the resultant yield across all growing regions. Hence, the mid-season dry spell is a crucial yield-determining risk factor. Because the spell occurs mid-season (from the end of January to mid March) it is termed the mid-season dry spell. Although it varies during any growing season, it may persist for four to six weeks.

In Table 5 we use the notion of mid-season dry spell and/or critical growth period to illustrate three cases: *under-match*, *exact-match* and *over-match*. In the case of an *under-match*, the optimal index month coincides with the month(s) of the growing season and may miss the critical growth period and mid-season dry spell. This could entail selection

of such months as January in a manner that enhances the basis risk, where indemnities are paid when in actual fact they are not supposed to be, and vice versa. In the case of an *exact-match*, the optimal index months (e.g. the month of February) coincide with the critical growth period. An *exact-match* is perhaps most desirable since it reduces basis risk. Finally, in the case of an *over-match*, the optimal index month coincides with periods well beyond the critical growth period range (e.g. the month of April). In this situation the seasonal outlook is known with near certainty.

Which index is better? As shown in Table 5, the rainfall index exhibits *exact-matches* for maize across most regions, but *under-matches* for cotton. The NDVI does not exhibit *exact-matches*, but nonetheless succeeds in *matching* the critical growth period across most maize-growing regions. Unlike the rainfall index, the NDVI exhibits *over-matches* across all cotton growing regions. This rather simple assessment helps to provide important insights: (a) an *under-match* could potentially entail huge costs due to its propensity to mismatch, and in this regard the rainfall index suffers a disadvantage; (b) both *exact-match* and *match* are equally desirable and hence both indices performed equally well; (c) in the case of an *over-match*, our results show that the NDVI mostly overshoots but, unlike the *under-match* case, the consequences are less severe, making the NDVI the preferred index; and (d), the NDVI exhibits comparatively higher loss-indemnity correlations across most maize-growing regions than rainfall, though the latter showed slightly better correlations for cotton.

Table 5: Mid-season risk-spell assessment: NDVI vs. rainfall index

Index	Crop	NR	Average loss-indemnity correlation		Dominantly selected optimal month		Mid-season risk spell assessment
			5%	10%	5%	10%	
NDVI	Maize	II	0.46	0.46	Mar	Feb	Match
		III	0.70	0.70	Mar	Feb	Match
		IV	0.70	0.70	Mar	Mar	Over-match
		V	0.69	0.69	Mar	Feb	Match
	Cotton	II	0.42	0.42	Feb	Apr	Over-match
		IV	0.52	0.52	Apr	Apr	Over-match
Rainfall	Maize	II	0.57	0.58	Jan	Jan	Under-match
		III	0.57	0.53	Feb	Feb	Exact-match
		IV	0.56	0.68	Feb	Feb	Exact-match
		V	0.39	0.44	Feb	Feb	Exact-match
	Cotton	II	0.65	0.65	Jan	Jan	Under-match
		IV	0.25	0.64	Jan	Jan	Under-match

5. SUMMARY AND CONCLUSION

Using historical maize and cotton yield data from nine districts in Zimbabwe, we find that catastrophic drought insurance contracts based on the NDVI can be constructed whose indemnities exhibit higher correlations with yield losses and whose fair premium rates lie in the affordable 5–10 per cent range. Except for a few districts, across both crops and most growing regions, the NDVI afforded appreciably higher-yield loss-indemnity correlations (0.40–0.90) than the rainfall index (0.25-0.70), implying that the former would embody lower basis risk.

With regard to assessing the sensitivity of the indices to detecting the mid-season dry spell, the NDVI predominantly selects the months of February–March for the maize crop and thus tends to *match* the critical growth period associated with the mid-season dry spell. For cotton, the NDVI predominantly picks the month of April and hence tends to *over-match* the critical growth period. With respect to the rainfall index, except in a few

instances, the correlations reflect *exact-match* with maize losses but tend to *under-match* cotton losses.

NDVI offers the additional advantage that they are measured using data provided by an internationally recognized agency, the NOAA, thus providing an element of security necessary for international reinsurers to offer index contracts. The rainfall index suffers a disadvantage in that it is drawn mostly from a sparsely distributed network of weather stations that often fail to capture the wide spatial crop losses. By contrast, this makes the satellite-derived NDVI a more desirable index as it comes with high spatial and temporal resolution, both essential for continuous monitoring and evaluation of crops during the growing season. We conclude that insofar as hedging against catastrophic drought events is concerned, the NDVI could be superior to the conventional rainfall index. Effective hedging against catastrophic drought risk using index insurance is one possible policy strategy that Zimbabwe could explore to address smallholder farmers' vulnerability to catastrophic droughts and food insecurity threats.

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