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Assessing the economic value of *El Niño*-based seasonal climate forecasts for smallholder farmers in Zimbabwe

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ABSTRACT: This study demonstrates the potential value of forecasts to smallholder farmers in Zimbabwe, the majority of whom often suffer severely from the impact of drought. Using crop simulation models to compare yield performances of farmers with and without forecasts, results indicate that, for a drought year, farmers with forecasts (WF) record higher yield gains (28%) compared to those without forecasts (WOF): in particular, farmers located in the most arid regions (NR V) recorded the highest yield gains (42%). A similar trend is observed during a neutral/average year, as farmers WF obtain predominantly higher yield gains (20%) than those WOF. However, during a good year, results show a different pattern as no yield gains are observed. In fact, farmers WOF perform better, suggesting forecasts in this case may not make much difference. Using gross margin analysis, results show farmers WF obtaining higher returns during a drought (US$ 0.14 ha^{-1}) and neutral year (US$ 0.43 ha^{-1}) but again not for a good year as farmers WOF outperform those WF. To summarize, forecasts can play an important role as loss-minimization instruments especially if the underlying year is an El Niño (drought) year. In conclusion, to attain full economic value of forecasts, complementary policies (currently missing) such as effective communication, improvement in forecast extension skills and promotion of farmer participatory and outreach activities could prove vital in enhancing the value of forecasts to smallholder farmers in general.

KEY WORDS seasonal forecasts; smallholder farmers; El Niño; economic value; drought risk; farmers with and without forecasts

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1. Background

Until recently, drought occurrence in southern Africa has been observed to be closely correlated with El Niño events that occur in the eastern tropical Pacific (Eastman and Anyamba, 1996; Mason and Jury, 1997). When sea surface temperature (SST) anomalies are high this causes warming of the ocean, resulting in a huge mass of warm water in the central and eastern tropical Pacific. This, in turn, affects atmospheric circulation, disturbs the normal pattern of air pressure, tropical rainfall and movement of the trade winds, leading to changes in weather patterns around the globe (Ropelewski and Halpert, 1987; NOAA, 1997). El Niño-Southern Oscillation (ENSO) events impose a strong influence on rainfall patterns and distribution in southern Africa. Their impact is strongest during the peak rainfall months of December to March (Mason and Jury, 1997). ENSO events often culminate in severe droughts. For instance, major droughts that affected the region (e.g., 1982/1983, 1986/1987, 1991/1992 and 2006/2007) are closely associated with El Niño episodes (WMO, 1995; Kogan, 1998).

In view of the increasingly better knowledge and understanding of ENSO events, it is now possible to predict major El Niño episodes at lead times of about 3–6 months (Mason, 1996). Today, many national departments of meteorology in southern Africa, under a collaborative regional climate forum called SARCOF (Southern African Regional Climate Outlook Forum), are collectively involved in monitoring ENSO events with the objective of providing seasonal forecast information to various end-users (water planners, policymakers, farmers, food organizations) and, especially, smallholder farmers. The forecasts denote rainfall probabilities presented in a three-pronged format (normal, above-normal and below-normal) for any pending season. These forecasts are routinely broadcast *via* the radio, TV, newspapers, farm bulletins and internet around early September, 1 month before the seasonal rain starts.

Although seasonal forecasts are being broadcast in Zimbabwe and in other countries in southern Africa, it is not yet well established how farmers, particularly smallholders, use forecasts to improve farm management practices as well as undertake strategic decisions to either avert/mitigate losses or exploit favorable weather conditions to optimize returns. If farmers can use forecasts to improve farm decisions, they not only reduce their vulnerability to El Niño effects but also their dependence on food aid, which often is subject to political abuse and uncertainty.

Climate variability is the most dominant source of food insecurity in southern Africa. With the majority of smallholder farmers dependent on rain-fed agriculture and vulnerable to climate variability, seasonal forecasts hold promise as a tool for drought mitigation and/or risk management. Essentially, seasonal forecasts offer farmers a realistic opportunity to manage climatic variability. With advance information on predicted seasonal outlook, smallholder farmers become better placed to handle climatic anomalies in ways that can reduce vulnerability to climate shocks. Specifically, smallholder farmers would be able to use seasonal forecasts as a tool to avert otherwise costly losses in the form of income, crop, animal and even human losses.

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Useful lessons can be drawn from past experiences of extreme drought events. For instance, the 1991/1992 extreme drought event left more than 100 million people (mostly smallholders) within the Southern African Development Community (SADC) severely affected and more than US$ 580 million worth of food aid had to be distributed under emergency measures to avoid massive hunger and starvation (SADC, 1993). In the case of Zimbabwe, the losses were more catastrophic as the smallholder farm sector lost more than 2 million head of cattle, the main source of draft power and capital wealth: crop yields dropped 54% below normal and the country had to survive on more than 2 million tons of cereals received as food aid (Makarau, 1992). To summarize, climate risks, especially drought, constitute a formidable barrier to investment and the adoption of high yield (but risky) technologies that have the potential to increase production and improve livelihoods of smallholder farmers.

1.1. Study motivation

Southern Africa is one part of the world likely to suffer disproportionately from the negative effects of climate change, in particular from the associated risks of extreme drought and flood events. The recently observed upsurge in extreme climate events across southern Africa bears testimony to some of these perceived impacts. Lobell *et al*. (2008) predict that southern Africa could lose more than 30% of its staple, maize, by 2030 due to climate change.

Extreme drought or flood events not only add to stresses on water resources, food insecurity and human health but are also largely responsible for constraining economic development in many countries across southern Africa. Indeed, most countries in this region are regarded as extremely vulnerable to climate change due to their over-dependency on rain-fed agriculture. Vulnerability to catastrophic climate events is worsened by the lack of coherent mitigation policies and concrete plans of action to deal effectively with climate change risks. In Zimbabwe, for instance, mitigation efforts have been largely focused on disseminating seasonal climate forecasts to end-users, especially smallholder farmers, but the impact of this policy has been largely minimal as seasonal forecasts remain widely un-adopted by smallholder farmers. In reality, however, many smallholders continue to face serious household food insecurity problems with a significant proportion being highly dependent on food aid and/or food handouts.

A fundamental question one may ask is why seasonal forecasts are not adopted by smallholder farmers in Zimbabwe (and equally by many other countries in southern Africa) where many continue to face serious food shortages, hunger, malnutrition and often life-threatening starvation. Plausible arguments which have been advanced to explain this include: skepticism of the forecasts due to past failures; ineffective communication; inappropriate format; lack of forecast extension skills and forecast education for smallholder farmers. In terms of skepticism, forecasts tend to suffer a credibility problem that arises mainly from the failure of past forecasts (Patt, 2001; Patt *et al*., 2005). Forecasts are not being communicated effectively to potential beneficiaries, especially smallholder farmers. Although forecasts are being disseminated in Zimbabwe, it is the art and skill of their communication that is largely missing, such as distilling, translating and transforming information to make it more manageable, user-friendly, understandable and beneficial to end-users. Seasonal forecasts are disseminated in probability undertones that may be difficult for a layman farmer to understand, and even if farmers do understand the probability forecasts, they probably do not know how to apply them to best advantage. With no forecast extension, farmers may lack the knowledge of how to apply forecasts for maximum benefit. Finally, smallholder farmers are faced with other more pressing constraints other than the availability or non-availability of seasonal forecasts. As Blench (1999) argues, it is too naïve to expect a farmer to gamble all their resources on a single best-bet strategy. Farm decision-making is an holistic approach and, hence, farmers could be facing more binding constraints than the mere non-availability of seasonal forecasts. Typically, smallholder farmers may be more concerned with issues such as when will the rainfall season start, what will the rainfall seasonal distribution look like, what crop varieties should be grown given the forecasts. These questions go beyond the mere dissemination of forecast information and necessitate the repackaging of seasonal forecasts to meet farmers' needs and expectations.

In sum, considerable effort has to be applied in developing forecast extension skills and farmer education to demonstrate the potential benefits to smallholder farmers. The creation of climate education centres, in developing countries in general, could mark a turning point in assisting smallholder farmers cope with climate-related risks and disasters.

1.2. Objectives

As motivated above, seasonal forecasts have had very minimal impact as they remain largely un-adopted by smallholder farmers in Zimbabwe. This occurs despite many smallholders facing serious food shortages, with a significant proportion perennially dependent on food-handouts. While studies in developed countries reveal that farmers benefit substantially from using seasonal forecasts (Easterling and Mjelde, 1987; Solow *et al*., 1998; Mjelde *et al*., 2000), the benefits of using seasonal forecasts by smallholder farmers in Zimbabwe (as well as other countries in southern Africa) is not yet well established (Vogel, 2000; Patt and Gwata, 2002; Makaudze, 2009).

Thus, the focus of this paper is on the assessment of the economic value of seasonal climate forecasts to smallholder farmers in Zimbabwe which might provide useful insights to policy-makers and facilitate more debate on seasonal forecasts and their potential role as risk mitigation tools. Such debates are more pertinent given the perceived climate change and its impact on millions of poor smallholder farmers in Zimbabwe and other countries in southern Africa.

The structure of the remainder of the paper deals with the methodology used for assessing the economic value of seasonal forecasts, a discussion of the data sources, a presentation of the simulation results derived from DSSAT v4 programme (Jones *et al*., 2004) and a final conclusion.

2. Methodology

In view of the discussion above, the key objective of the study is to assess the economic value of seasonal forecasts to smallholder farmers in Zimbabwe. Forecast information is useful when it helps the decision-maker change course, from a less informed to a more informed position. In the context of a farmer, a change of course could mean altering management decisions such as changing fertilizer amounts, cultivar type, planting date and plant population, among other issues. However, to do this the presumption is that new information incorporated into the agent's decision-making function must alter management decisions. In other words, management decisions become altered only as a function of new information received. Thus, a decision process is characterized by the new information about a stochastic event and how this interacts with those variables under the decision-maker's control.

There is a growing body of literature on the economic valuation of seasonal forecasts, starting from theoretical underpinnings of decision-making under uncertainty to the valuation of forecasts on the basis of *ex ante* approaches (Mjelde and Dixon, 1993; Meza *et al*., 2003; Hansen *et al*., 2006). *Ex ante* approaches value seasonal forecasts using predictive models that simulate a stochastic event (e.g. rainfall) and numerous examples are found in literature (Mjelde *et al*., 2000; Reyes *et al*., 2009; Hansen *et al*., 2010). Although in general, *ex ante* approaches are informative, they can only offer a limited valuation of what the forecast information is plausibly worth, because they are largely normative (Msangi *et al*., 2006).

To construct the valuation model, one can start by discussing the household decision-making theory using the framework suggested by Rubas *et al*. (2006), who cast a decision-maker using forecasts to influence farm decisions with the aim of maximizing the underlying utility objective. Decision theory assumes that preferences among risky alternatives can be described by the maximization of a utility function. To present the model mathematically, assume the farmer's problem is to maximize expected utility by choosing from a decision set using only prior knowledge. Mathematically this can be generalized as:

$$u(H) = \max_{D} E_{\mathrm{c}}[u(D, c)h(c)] \tag{1}$$

where max is the maximization operator, $u(H)$ is the maximum expected utility using climatological information; E_{c} represents expectation operator for the range of climate conditions of interest, c; $h(c)$ represents the historical probability density function of climate conditions; u denotes the utility function and D the decision set. Embedded within this equation are all other aspects that affect the decision process, such as risk aversion, institutional factors and others.

When climate forecasts (F_i) become available, the probability density function of climate conditions is represented by $g(c|F_i)$. The decision maker's maximization problem becomes:

$$u_i(F_i) = \max_{D} E_{(c|F_i)}[u(D, c)g(c|F_i)] \tag{2}$$

where i represents the forecasts and F_i represents one of the many possible forecasts. Expected utility covering the entire forecast system, F, can be written as:

$$u(F) = \max_{D} E[u_i(F_i)Z(F_i)] \tag{3}$$

where $Z(F_i)$ is the probability density function associated with the probability of each forecast.

Therefore, the value of the forecast system is:

$$V = u(F) - u(H) \tag{4}$$

where V represents the difference between the expected utility with the use of seasonal forecasts *versus* the expected utility using only prior knowledge. If V is in utility terms, the difference in utility can be converted into monetary units using certainty equivalence dollars (Mjelde and Dixon, 1993). If risk neutrality is assumed, V could be interpreted in monetary units. With the above approach, one is able to assess the value of using climate forecasts.

Figure 1 illustrates a dateline of activities showing forecast signals and the decision-making processes of a typical smallholder farmer in Zimbabwe. The activity sequence is as follows: (1) the rainfall season starts at the end of October, peaks to maximum during January and February before it gradually declines during March and ends in April; (2) by the end of August the national department of meteorology broadcasts forecasts for a pending season predicting rainfall outlook; upon receiving the forecasts, a farmer makes crucial farm decisions such as the size of land to cultivate, the selection of crop cultivars, the fertilizer quantities to purchase, crop rotation and so on; (3) forecasts are issued covering two growth stages: stage 1 refers to the first 3 months during the growing season (October-November-December (OND)), a period which relates to early germination and initial crop growth, and stage 2 refers to the subsequent months of January-February-March (JFM), the most critical phase in the crop growth cycle covering crop flowering, pollination, grain-filling, maturation and resultant yield. Further, because forecasts are offered in two stages (OND and JFM) this provides the farmer with the flexibility to modify actions, and (4) harvest time (April to May) ends with the realization of the final seasonal output.

Seasonal climate forecasts have been broadcast/disseminated in Zimbabwe (and likewise most countries in southern Africa) since the 1997/1998 season. As discussed earlier, the forecasts are routinely broadcast during August *via* several communication channels (radio, TV, print media, internet). As shown in Table 1, the forecasts are issued as a three-pronged probability format that underlies the likelihood of the season being an above normal (good), below normal (bad) and a near-normal (neutral) year. (Above-normal rainfall is defined as the wettest 33.3% of recorded rainfall amounts in each zone, normal is defined as the middle 33.3% of the amounts and below normal rainfall is the driest 33.3% of recorded rainfall amounts.)

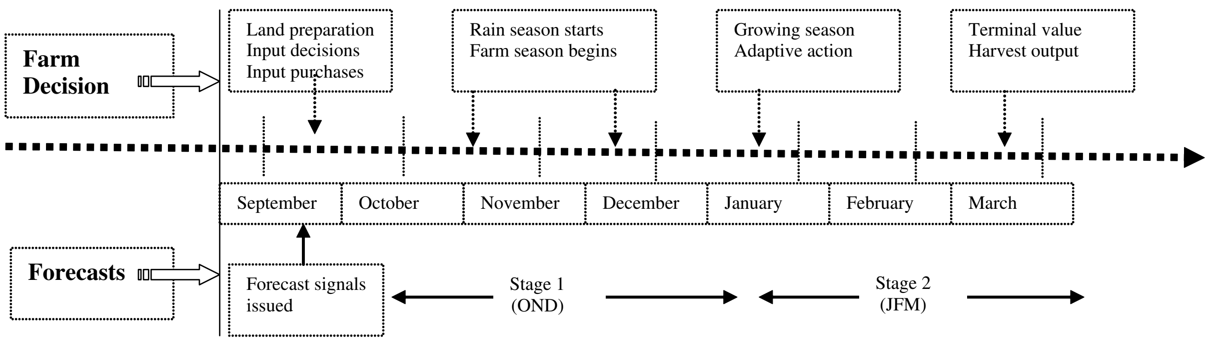

Figure 1. Dateline of forecasts, growing season and realized output.

Table 1. Seasonal forecasts issued by Drought Monitoring Centre for growing season 1997/1998 to 2011/2012.

Season	ENSO signal	Rainfall forecast probability					
		Oct-Nov-Dec			Jan-Feb-Mar		
		Above_N	Normal	Below_N	Above_N	Normal	Below_N
1997–1998	El Niño	0.20	0.40	0.40	0.13	0.35	0.53
1998–1999[a]	–	–	–	–	–	–	–
1999–2000	La Niña	0.37	0.40	0.23	0.40	0.37	0.23
2000–2001	La Niña	0.45	0.33	0.25	0.35	0.45	0.20
2001–2002	Neutral	0.35	0.425	0.23	0.30	0.50	0.20
2002–2003	El Niño	0.30	0.40	0.30	0.25	0.40	0.35
2003–2004	Neutral	0.33	0.43	0.25	0.28	0.40	0.33
2004–2005	La Niña	0.30	0.40	0.30	0.25	0.40	0.35
2005–2006	Neutral	0.40	0.35	0.25	0.35	0.40	0.25
2006–2007	El Niño	0.25	0.40	0.35	0.30	0.40	0.30
2007–2008	La Niña	0.35	0.40	0.25	0.38	0.38	0.25
2008–2009	Neutral	0.30	0.40	0.30	0.30	0.40	0.30
2009–2010	El Niño	0.30	0.40	0.30	0.30	0.40	0.30
2010–2011	La Niña	0.35	0.40	0.25	0.35	0.40	0.25
2011–2012	El Niño	0.25	0.40	0.35	0.40	0.35	0.25

[a] Missing information. Source: Adapted from SARCOF statistics.

3. Data sources and assumptions

The study used two types of data: technical crop input and daily weather data. Technical crop input data (shown in Tables S1–S3) were obtained from two sources: the departments of Research and Specialist Services (R and SS) and Agricultural Technical and Extension Services (AGRITEX). Because of the diverse agro-ecological, soil and climatic conditions prevailing across Zimbabwe's landscape, the departments of R and SS and AGRITEX have developed detailed crop input management handbooks that provide extensive technical details which document suitable cultivars, appropriate fertilizers/herbicides/chemical application rates, ideal planting dates, proper plant space and plant population (see Tables S1–S3). The data illustrates the recommended input levels across different agro-ecological regions that allow the attainment of feasible optimal yields, under ideal climatic conditions. This is referred to as 'traditional farm management' practice throughout this paper.

The second type of data includes the daily weather data on rainfall, temperature (minimum and maximum), solar radiation and evapotranspiration, obtained from the national department of meteorology. The data are obtained for three typical seasons that represent a drought/bad (El Niño), a good (La Niña) and an average (neutral) season. In this regard, three specific seasons (1991/1992, 2003/2004 and 2004/2005) are selected that typically exemplify a bad, good and average season, respectively. The data are obtained for four weather stations (Harare, Masvingo, Mutoko and Bulawayo) each being a representative of agro-ecological region II, III, IV and V, respectively. (Zimbabwe is divided into five agro-ecological or natural regions (NR) numbered I to V and which indicate potential in terms of soil fertility, rainfall, soil-water balance and moisture, which decreases as one ascends to higher regions from NR I to NR V) Due to data constraints, analysis is limited only to maize, the main staple.

The DSSAT v4 programme was used to run the various maize simulations based on different weather conditions and management practices. A key feature of DSSAT is the 'cropping system model' (CSM) that simulates crop growth and development over time for individual crops based on phenology, daily growth, plant nitrogen and carbon demand and senescence. The DSSAT-CSM model requires three key inputs: weather input, management input and soil input.

'Weather input' is essential for generating daily data for weather variables (e.g., maximum and minimum temperatures, solar radiation, precipitation, relative humidity, wind speed). 'Soil input' consists of three components: soil dynamics, which computes soil characteristics, soil water, which computes soil water processes including infiltration, runoff and water-table depth, and soil nitrogen and carbon which computes soil nitrogen and carbon processes, including organic and inorganic fertilizers. 'Management input' characterizes when to plant, harvest, apply inorganic fertilizers, apply crop residue and organic materials, and to irrigate.

Seasonal forecasts are incorporated in the DSSAT programme *via* the 'management input' options. Because management input offers a user the flexibility to alter management practices, this provides an ideal option to explore the potential impact of seasonal forecasts on yield outcomes. In this case, three management practices are analysed based on forecasts predictions: change planting date; change crop variety and change fertilizer amounts. For instance, if forecasts predict a below-normal (or bad) season, farmers with forecasts (WF) can alter management practices by planting early, growing short-season and drought-resistant varieties, applying minimal amounts of fertilizers, and so on. In contrast, farmers without forecasts (WOF) rely on traditional management practices and in addition, drawing from own knowledge and experience. Comparing yield performances between farmers WF and WOF, obtainable under different management practices that characterize different weather conditions, the paper establishes the potential economic value of seasonal forecasts from the smallholder farmers' perspective.

To keep the analysis tractable, some simplifying assumptions are necessary. First, farmers WF are using the forecast information for farm management decisions that optimize net returns (yield *per* hectare, t ha^{-1}, or net gross margin, US\$ ha^{-1}). Second, farmers WOF rely on historical traditional knowledge and experience to formulate management decisions that maximize net returns (yield *per* hectare, t ha^{-1}, or net gross margin, US\$ ha^{-1}). Traditional management practices include detailed technical information provided by agronomic experts (as discussed earlier). Third, for both categories of farmers (WF and WOF), no herbicides, insecticides or other chemicals are applied in the production process. Fourth, no labour costs are considered. Fifth, a farmer's risk behaviour is embedded in the decision-making process. Sixth, assuming profit motive, each farmer (whether WF or WOF) pursues an input strategy that seeks to maximize the final outcome, referred to as optimal input strategy throughout the paper. Alternatively, a farmer can pursue an input strategy where no inputs (fertilizers/chemicals/insecticides) are applied, referred to as zero-input strategy. Finally, all simulations are performed under the presumption that forecast information is perfect.

4. Discussion of results

This section presents the main results of the study. The results show how maize yield changes in response to varying farm management practices based on with and without forecasts assumptions (discussed earlier). The simulations are run based on three farm management practices: change planting dates, change crop cultivars and change fertilizer application rates. The simulations are repeated for different seasons that exemplify a bad (El Niño), good (La Niña) and an average (neutral) year.

The first results illustrate simulated maize yields obtained under weather conditions that characterize a drought year (1991/1992) and are based on altering three management practices (change planting dates, cultivar choice and fertilizer application rates) showcasing both WF and WOF farmers. The second and third cases are replicates of the first but performed under weather conditions that underlie a neutral (2003/2004) and good (2004/2005) season, respectively. In each case, observed changes in maize yields are recorded for the selected representative districts (Harare, Masvingo, Mutoko and Bulawayo) drawn from NRs II, III, IV and V respectively. Using this approach, three performance indicators (yield gains/losses; net gross margin; return *per* dollar invested) that underpin the economic value of seasonal forecasts are derived and compared across regions/districts between WF and WOF farmers.

4.1. First simulation results based on a drought year (1991/1992)

The first round of results (Table 2) show maize yields gains/losses across different agro-ecological regions for a selected typical drought season, 1991/1992. Starting with wet agro-ecological NR II (Harare district), results indicate that under an optimal input management strategy, by planting early farmers WF realize higher yields of 3.03 and 2.26 t ha^{-1} on medium and long season maize varieties, respectively, which translate to 13 and 7% higher yield performance than farmers WOF but, in contrast, if a farmer WF responds by planting late, s/he realizes lower yield levels of 0.94 and 2.05 t ha^{-1} on long- and medium-season varieties, respectively, compared to farmers WOF, who are realizing higher yield levels (1.33 and 2.69 t ha^{-1}) for the same varieties. The results suggest that forecast information yields no additional value if it involves late planting, especially in the wet regions NR II. The result is sensible given the long- and medium-season varieties would require longer days-to-maturity (145–170 days) which may not be possible given late planting.

Under the zero-input management strategy, results show that by planting early, farmers WF do realize higher yield gains on both long (0.03) and medium-season (0.14) varieties than WOF counterparts. However, similar to the observation above there are no yield gains if farmers WF plant late compared to farmers WOF.

With respect to semi-arid agro-ecological NR III (Masvingo district), results indicate that under optimal input strategy, WF farmers obtain higher yields by either planting early or late compared to their WOF counterparts. By planting early, WF farmers obtain higher yields of 13 and 29% on short- and medium-season varieties, respectively. On the other hand, by

Table 2. Observed changes in maize yield for farmers WF and WOF under three management strategies during a typical drought season (1991/1992).

Season	District	Δ Management strategies					Yield gain/loss	
		Δ Fertilizer application	Δ Maize variety	ΔPlanting date			% Δ	
				With forecasts (t ha^{-1})		Without forecasts (t ha^{-1})		
1991/1992				Early planting	Late planting	Traditional planting	Early	Late
	NR II (Harare)	Optimal-input	Long	2.26	0.94	1.33	0.70	−0.29
			Medium	3.03	2.05	2.69	0.13	−0.24
		Zero-input	Long	1.09	0.71	1.06	0.03	−0.33
			Medium	1.32	0.97	1.16	0.14	−0.16
	NR III (Masvingo)							
		Optimal-input	Medium	1.83	1.90	1.42	0.29	0.34
			Short	1.59	1.41	1.37	0.16	0.03
		Zero-input	Medium	0.74	0.55	0.55	0.35	0.00
			Short	0.45	0.35	0.37	0.22	−0.05
	NR IV (Mutoko)							
		Optimal-input	Medium	2.53	2.42	2.72	−0.07	−0.11
			Short	1.65	1.62	1.10	0.50	0.47
		Zero-input	Medium	0.90	0.77	0.73	0.23	0.05
			Short	0.52	0.52	0.46	0.13	0.13
	NR V (Bulawayo)							
		Optimal-input	Short	1.78	1.76	1.59	0.12	0.11
		Zero-input	Short	0.28	0.12	0.15	0.87	−0.20

planting late WF farmers obtain higher yield gains of 3 and 34% on short- and medium-season varieties, respectively. This practice of planting early and/or late can be viewed as a risk spreading or diversification strategy by farmers WF who may choose to stagger planting dates so as overcome early or mid-season dry-spell risks. It is important to emphasize that for farmers WF all these decisions are being influenced and guided by forecast signals. Under the zero input strategy, results show yield gains for early planting on both medium- (35%) and short-season (22%) varieties. However, there are no yield gains for late planting. Figure 2 provides an overview of these results.

The results for the driest and most arid agro-ecological regions, NR IV and V, show WF farmers recording yield gains by either planting early or late and mostly for the short-season varieties. In particular, the highest yield gain (87%) is recorded in NR V under the zero-input strategy. This big difference in yield gains emphasizes the potentially important role forecasts could play as drought mitigation tools especially in arid regions, where most farmers are located and suffer severely due to drought impact.

4.2. Second simulation results based on neutral (average) year (2003/2004)

The second run of simulations replicates the first case (discussed above) but under different weather conditions that characterize a neutral/average year (2003/2004). Figure 3 presents a graphical view of the results. Looking at wet region, NR II, farmers WF realize significant yield gains on both long- and medium-season varieties by either planting early or late compared to a counterpart WOF. The highest yield gain (115%) is recorded on long-season varieties when farmers plant late under the optimal input strategy. Under the zero-input strategy, yield gains are realized on long-season varieties for both early and late planting, unlike for the medium-season varieties.

The results for NR III show no yield gains (under the optimal input strategy) whether by planting early or late, but modest yield gains are observed under the zero-input case during both early and late planting. The results for NR IV show no yield gains accruing to WF farmers either by planting early or late under both the optimal and the zero-input management strategies. In the case of the driest NR, V, short-season varieties

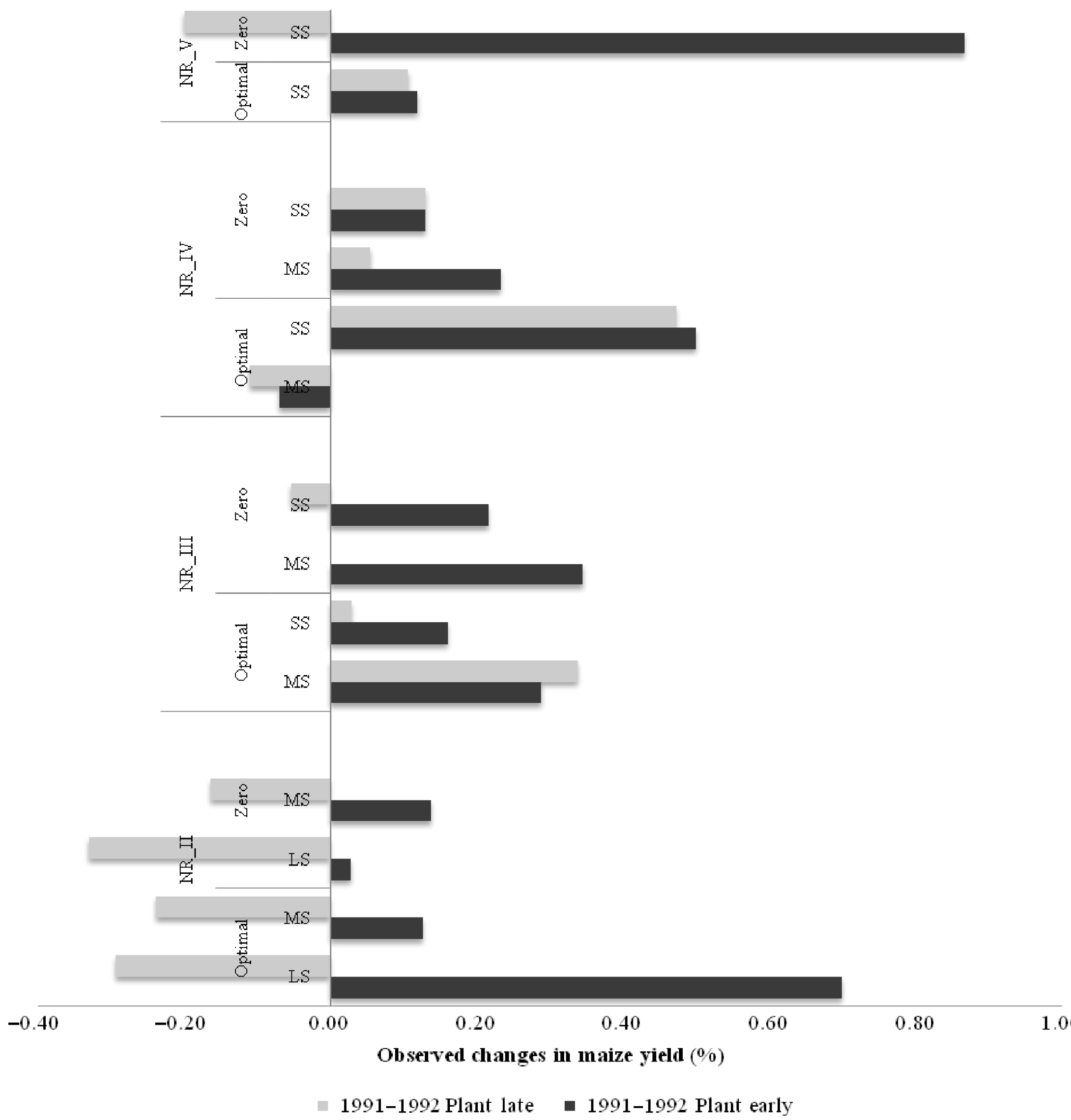

Figure 2. Observed maize yield gain/loss by natural regions (NR II–V) for long (LS), medium (MS) and short (SS) season varieties under optimal-input and zero-input strategies in 1991–1992 (drought/*El Niño* season).

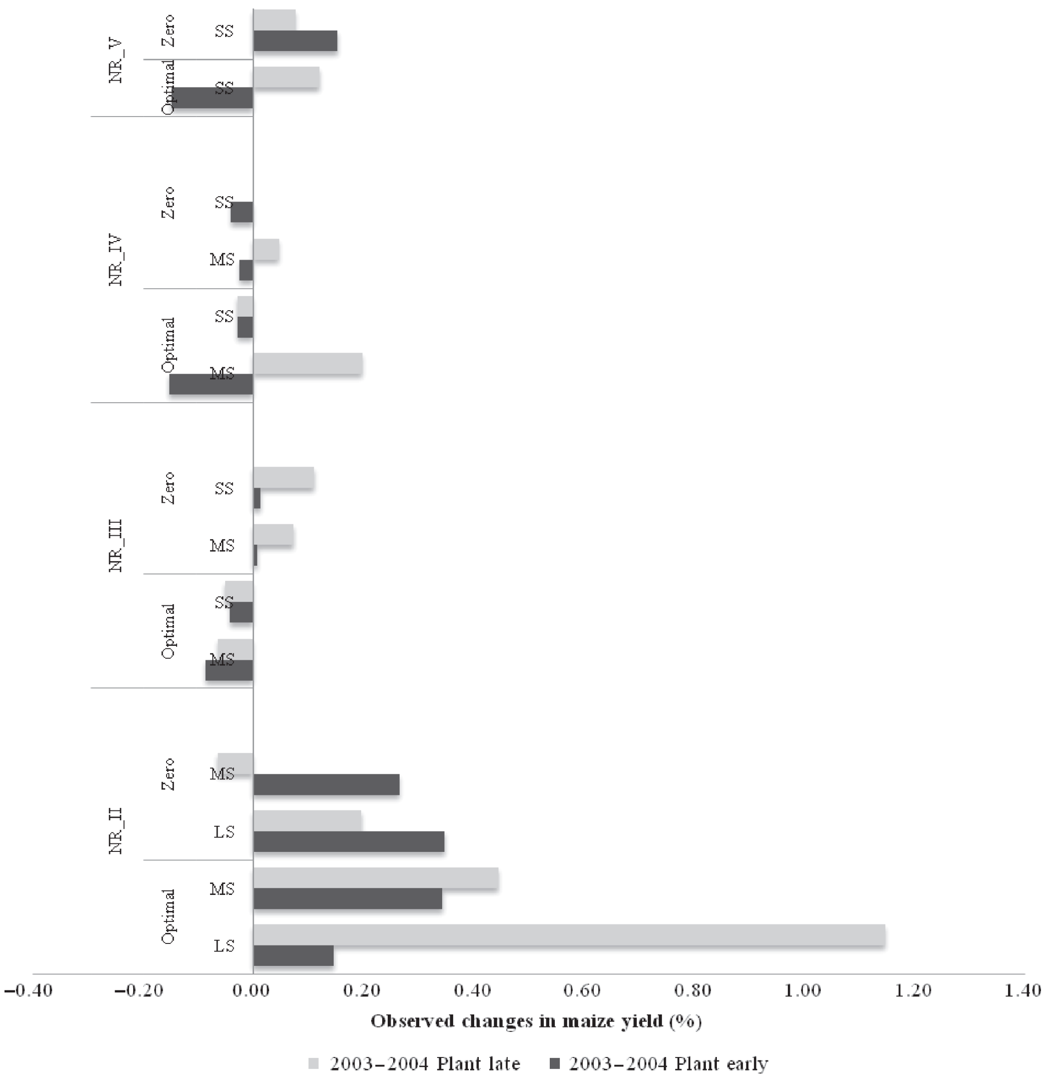

Figure 3. Observed maize yield gain/loss by natural regions (NR II–V) for long (LS), medium (MS) and short (SS) season varieties under optimal- input and zero-input strategies in 2003–2004 (average season).

show positive yield gains mostly under the zero-input strategy for both early and late planting (see also Table S4).

4.3. Third simulation results based on good year (2004/2005)

The third run of simulation results are based on weather conditions that characterize a good rainfall season with results shown in Figure 4. As expected, most regions (except arid NR V) record high yields *per* hectare due to favourable weather conditions. However, results show farmers WF failing to outperform counterparts WOF as there are no yield gains across most regions. For instance, the long-season varieties show no yield gains by either planting early or late in NR II under the optimal input strategy. It is only the medium-season varieties that record significant yield gains.

The pattern is also true for NR III where (except for the medium-season variety) the short-season variety fails to dominate under both optimal- and zero- input strategies for WF farmers. These observations are the same for NR IV (except for the zero-input strategy) as there are no significant yield gains for WF farmer. Likewise, a similar pattern is observed in arid NR V, where results indicate no yield gains for either early or late planting under both the optimal- and zero-input strategies (see also Table S5).

In sum, the simulation results discussed above indicate the following. For a good rainfall season, regardless of whether pursuing an optimal- or zero- input strategy, farmers WF across most regions record no significant yield gains compared to counterparts WOF. The opposite is true during a bad rainfall season, as farmers WF obtain higher yield gains, especially following early planting. For a neutral/average season, while most regions record no significant gains, it is in NR II where higher yield gains are recorded.

4.4. Value assessment of seasonal forecasts

Based on the simulation results above, the final section presents an assessment of the economic value of seasonal climate forecasts to smallholder farmers. For this purpose, two indicators are derived and used to gauge the economic value of forecasts: net yield gain/loss based on WF/WOF, and gross margin net return *per* dollar invested (US\$ ha^{-1}).

4.4.1. Value assessment using net yield gains/losses

Using WF/WOF results based on the optimal- and zero-input management strategies discussed above, net yield gain/loss

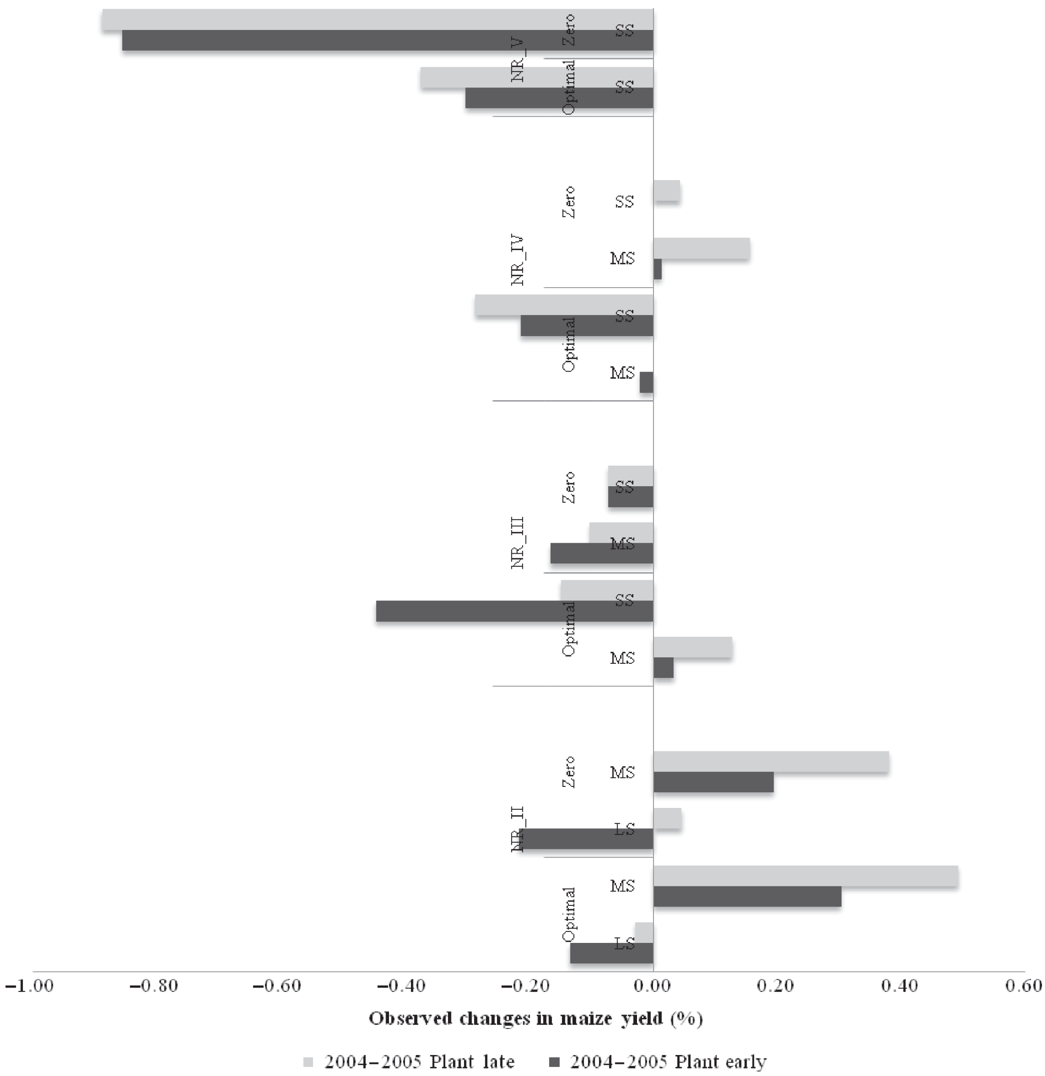

Figure 4. Observed maize yield gain/loss by natural regions (NR II–V) for long (LS)-, medium (MS)- and short (SS)-season varieties under optimal-input and zero-input strategies in 2004–2005 (*La Niña*/good season).

across growing seasons (bad, good and average) and agro-ecological regions (NR II–V) are computed and summarized in Table 3. From the results, the following observations are made. The highest overall net yield gain (28%) is recorded during the drought year (1991/1992); this is followed by yield gain of 20% during an average/neutral year (2003/2004); no yield gains (−31%) are recorded during a good year (2004/2005). In addition, the following observations can be made: for a drought year, NR V records the highest yield gain (49%); while for a good year, there are no yield gains observed across most regions except in NR II where high yield gains are recorded (26 and 71%) for both early and late planting.

The results underscore some important implications. Seasonal forecasts are potentially of great value for farmers located in the most arid regions (NR V) particularly during a drought (El Niño) year. Except for NR II, all regions record negative yield gains during a good year (La Niña), implying that forecasts may not make much difference given a good year. It is only in wetter NR II that forecasts matter most during a good year. This is sensible, as farmers in better agro-ecological regions would exploit the available forecast information to optimize returns for a predicted good year. When aggregated across all seasons and regions, farmers WF are better off overall, as they realize a net yield gain of 17.7% compared to farmers WOF.

4.4.2. *Value assessment using net margin return (US$ ha^{-1})*

The second approach to valuing seasonal forecasts involves using gross margin analysis. The detailed gross margin values (US$ ha^{-1}) based on simulated maize yields for the bad, good and neutral seasons are shown in Table S6. A summary of the net return gross margin values are shown in Table 4. The results indicate that for a drought year (1991/1992), WF farmers growing medium-season varieties realize the highest overall net return of US$ 0.52 ha^{-1} compared to WOF counterparts who realize US$ 0.26 ha^{-1}, but this is not the case with long-season varieties as both WF and WOF farmers incur losses of US$ 0.10 ha^{-1} and US$ 0.46 ha^{-1}, respectively. This result indicates that although both categories of farmers suffer losses due to drought, it is those WOF who suffer most. In particular, farmers WOF located in higher agriculturally potential regions (NR II), growing long-season varieties, are the worst affected.

For short-season varieties, on the other hand, farmers WF realize modest net returns of US$ 0.04 ha^{-1} compared to losses

Table 3. WF/WOF proportionate maize yield changes by natural region (NR) for the selected seasons.

Season	WF yield gain/loss				Overall
	NR	Early planting	Late planting	Net	
1991/1992	II	0.25	−0.26	−0.01	–
	III	0.25	0.08	0.33	–
	IV	0.20	0.14	0.34	–
	V	0.49	−0.05	0.41	0.28
2003/2004	II	0.28	0.43	0.71	–
	III	−0.03	0.02	−0.01	–
	IV	−0.06	0.05	−0.01	–
	V	0.00	0.10	0.10	0.20
2004/2005	II	0.04	0.22	0.26	–
	III	−0.16	−0.05	−0.21	–
	IV	−0.06	−0.02	−0.08	–
	V	−0.58	−0.63	−1.21	−0.31

to farmers WOF (US\$ 0.25 ha^{-1}). When aggregated across all varieties, results show farmers WF realizing overall net returns of US\$ 0.14 ha^{-1}, unlike their WOF counterparts who incur negative returns (US\$ 0.15 ha^{-1}). A rather important message the results imply is that farmers with forecasts will have the ability to undertake strategic decisions to help avert otherwise severe losses, particularly during extreme drought years.

For a neutral year (2003/2004), results show both WF and WOF farmers recording mostly positive net returns. However, farmers WF are predominantly realizing higher overall net returns for all varieties. In particular, the medium-season varieties record the highest net returns (US\$ 0.94 ha^{-1}), followed by short-season varieties (US\$ 0.28 ha^{-1}), with the long-season varieties recording the lowest net returns (US\$ 0.08 ha^{-1}). Similar to the observations above, farmers WOF growing long-season varieties (those in NR II) experience the heaviest losses, of US\$ 0.46 ha^{-1}. Overall net results indicate farmers WF realize three times more returns (US\$ 0.45 ha^{-1}) than farmers WOF (US\$ 0.15 ha^{-1}).

Results for a good year (2004/2005) show a different picture compared to the drought and neutral seasons discussed above. In this case, farmers WOF realize higher returns on all varieties (except medium) and across most regions. Specifically, short- and long-season varieties record higher net returns of US\$ 0.62 and 0.55 ha^{-1} respectively. Overall results indicate farmers WOF realize higher net returns of US\$ 0.85 ha^{-1} compared to their WF counterparts (US\$ 0.75 ha^{-1}). Because farmers WOF outperform their counterparts WF, the result suggests that forecasts may not make much difference during a good year.

5. Conclusions

This study demonstrates the potential value of seasonal forecasts to smallholder farmers in Zimbabwe, the majority of whom endure heavy losses due to adverse weather, particularly drought. Some important insights can be drawn from the study. First, if the underlying season is a bad one (implying an El Niño year), forecasts play an important role as ‘loss-mitigation’ instruments. As the results indicate, by changing planting dates (early/late), applying appropriate fertilizer rates (optimal/zero) and using suitable maize cultivars (short-, medium- and long-season varieties) farmers with seasonal forecasts (WF) are able to reduce and/or minimize yield losses across most regions. In particular, losses could be severe for farmers in the better agro-ecological region (NR II), who are bound to invest substantial amounts of money in inputs (seeds, fertilizers, chemicals).

Second, forecasts are likely to promote ‘strategic-behaviour’ which could prove vital for reducing vulnerability of smallholder farmers to catastrophic drought events. As implied by the results, this is particularly true in arid regions NR IV–V, where, by engaging in zero-input strategy and growing short-season varieties, farmers WF are able to realize positive yield gains despite an extreme drought season.

Third, if, on the other hand, the underlying season is a good year, no yield gains are observed across most regions (except NR II), suggesting that forecasts may not make much difference.

In conclusion, to attain full economic value of forecasts, complementary policies (currently missing) such as effective communication, improvement in forecast extension skills, forecast education and promotion of farmer participatory and outreach activities, could prove vital in enhancing the value of forecasts to smallholder farmers in Zimbabwe and many other African countries.

Table 4. Comparison of net return values (\$ ha^{-1}) by natural region (II–V) for selected growing seasons between WF/WOF.

Season	Variety	Net return (\$ ha^{-1})								Overall	
		V		IV		III		II			
		WF	WOF	WF	WOF	WF	WOF	WF	WOF	WF	WOF
1991/1992	SS	0.21	0.09	−0.01	−0.08	−0.15	−0.26	–	–	0.04	−0.25
	MS	–	–	0.34	0.43	−0.07	−0.29	0.25	0.12	0.52	0.26
	LS	–	–	–	–	–	–	−0.10	−0.46	−0.10	−0.46
Net										0.14	−0.15
2003/2004	SS	0.14	0.03	0.04	0.07	0.10	0.14	–	–	0.28	0.24
	MS	–	–	0.49	0.27	0.71	0.81	−0.26	−0.48	0.94	0.69
	LS	–	–	–	–	–	–	0.08	−0.47	0.08	−0.47
Net										0.43	0.15
2004/2005	SS	−0.19	0.13	−0.09	0.14	0.16	0.35	–	–	−0.12	0.62
	MS	–	–	0.44	0.46	0.75	0.58	0.80	0.34	1.99	1.38
	LS	–	–	–	–	–	–	0.44	0.55	0.44	0.55
Net										0.77	0.85

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Supporting information

The following supporting information is available as part of the online article:

Table S1. Maize recommended optimal fertilizer application rates and planting date.

Table S2. Maize hybrid variety characteristics and suitability by natural regions (NRII–V).

Table S3. Maize plant spacing and population recommendations for attainment of optimal yield.

Table S4. Observed changes in maize yield for farmers WF and WOF under three management strategies during a typical good season (2004/2005).

Table S5. Observed changes in maize yield for farmers WF and WOF under three management strategies during a typical good season (2004/2005).

Table S6. Gross margins and net return for selected growing seasons (bad, neutral, good).

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