The Potential Impacts of the Use of Southern Oscillation Information on the Texas Aggregate Sorghum Production

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(Manuscript received 23 April 1997, in final form 20 March 1998)

ABSTRACT

Economic decision models incorporating biophysical simulation models are used to examine the impact of the use of Southern Oscillation (SO) information on sorghum production in Texas. Production for 18 sites is aggregated to examine the impact of the use of SO information on the aggregate supply curve and other production and economic variables. Two information scenarios are examined. For all expected prices, the use of SO information increased producers' net returns over the scenario in which SO information is not used. Depending on price, the expected Texas aggregate sorghum supply curve using SO information shifted both left and right of the without SO information supply curve. Changes in nitrogen use based on the SO information is a major factor causing the shift in the supply curves. Further, the use of SO information decreased aggregate expected costs per metric ton of production. Changes associated with the use of SO information can be summarized as follows: the use of SO information provides producers a method to use inputs more efficiently. This more efficient use has implications for both the environment and for the agricultural sector.

1. Introduction

Agricultural decision makers have always been concerned about climate variability because of its effect on decision makers' and societies' welfare. Though climatic events are uncontrollable, climate forecasts may assist decision makers in coping with the variability (Sonka et al. 1988; Mjelde et al. 1993). There is evidence that climate forecasting skill is improving (Australian Bureau of Meteorology 1991; Livezey 1990). One phenomenon receiving considerable attention as a potential factor capable of improving forecasting skill is the El Niño–Southern Oscillation (ENSO) (Cane 1983). The Southern Oscillation (SO) has been identified as one of the most prominent signals of year-to-year climate variability (Rasmussen and Wallace 1983). Variations in SO patterns have been correlated with seasonal climate patterns months prior to their occurrence for various regions of the world (Stone et al. 1996). This correlation has been linked to variations in crop yields in certain regions of the world (Cane et al. 1994; Mjelde and Keplinger 1998; Nicholls 1986).

The use of ENSO-based climate forecasts is not just a matter of academic interest. Australian decision makers are encouraged to use tools such as Rainman to estimate location-specific precipitation, frost, and temperature probabilities based on the SO (Australian Bureau of Meteorology 1998). Decision makers in Peru have incorporated SO forecasts into their national agricultural policy (Lagus and Buzier 1992). Glantz (1994) states, ''only recently have international agencies coping with food security problems in Southern and Northeastern African come to realize the potential value of El Niño forecasts.'' One reason for the increased use of ENSO forecasts is our increased knowledge concerning this phenomenon. A major contributor to our increased understanding is the recently completed 10-yr multinational Tropical Ocean Global Atmosphere program (Webster and Lukas 1992; Trenbeth and Kiehl 1997). To capitalize on our increased understanding and to fur-

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ther the development of climate forecasting, the United States and 15 other countries have formed an International Research Institute for Climate Prediction. One of the institute's objectives is the application of climate forecasts to explicit social and economic issues (Glantz 1996).

Individual producers could conceivably use improved climate forecasts based on the SO to modify their production practices to increase profitability. The cumulative impact of producers modifying their production decisions may shift regional and national supply curves. Shifts in the supply curves have ramifications for the agriculture sector. There are, however, few studies that have examined the impact of climate forecasts at aggregation levels beyond the firm. One such study is Adams et al. (1995), which estimated the potential effects of the use of SO information in southeastern U.S. agriculture. Their study indicates that because of price decreases producers lose, but consumers and society overall gain, from the use of climate forecasts. Other studies examining the impact of climate forecasts at the sector level, in general, indicate a rightward shift of the supply curve (Lave 1963; Greenburg 1976; Babcock 1990). Given the nature of the agricultural sector, results of these studies are similar to Adams et al.'s. None of these studies address in any detail the development of the aggregated supply curves with and without the use of climate forecasts. At the firm level, many studies, however, suggest without price changes producers net revenues will increase as climate forecasts are incorporated into the decision making process. For reviews of this literature see Mjelde et al. (1989), GCOS Working Group (1995), and Nicholls (1996).

This study's objective is to address this deficiency in the literature concerning the development of aggregate supply curves for use in sector-level modeling. Expected state-level supply curves for dryland sorghum are developed from hectare-level economic models. Supply curves are developed assuming sorghum producers do not use SO information and assuming they use the information. The hectare-level models allow the producer to vary production inputs (hectares planted, planting date, applied nitrogen, cultivar type, and planting density) based on SO information. Changes in production practices caused by the use of the SO information leads to changes in per hectare sorghum yields, which in turn lead to changes in the state-level sorghum supply curve. A simulation model provides the basis for the study. To account for geographical, biophysical, and meteorological differences across the state, 18 sites within the state are modeled. Texas is used as the study site because 1) it has been shown climate conditions in at least part of Texas are impacted by the SO (Ropelewski and Halpert 1986, 1987, 1989) and 2) a correlation between state-level sorghum yields and the SO has been established (Mjelde and Keplinger 1998). In addition to examining potential changes in the supply curves, the impacts of the use of SO information on aggregate input use, costs, and net returns are examined.

2. Methodology for deriving state-level supply curve

To derive the state-level dryland sorghum supply curve for Texas, the following methodology is used. Eighteen sites across Texas are used to represent regional sorghum production. Production at these sites based on the producer's use of SO information is obtained through the use of an economic decision model. Embedded within this decision model is a biophysical simulation model of sorghum growth that requires daily weather data. The site-level production is then aggregated by the number of hectares each site represents to obtain the aggregate sorghum supply curve. A similar aggregation approach is used to obtain the impacts on expected aggregate nitrogen use, costs, net returns, and planted hectares.

a. The economic model

To obtain the optimal production practices for each site, two hectare-level decision models are developed for each site. The first model assumes the producer does not use any knowledge of the SO. In this model, the producer is assumed to use optimal input combinations derived from using 43 yr of climatological data. Further, it is assumed each year is equally likely. A single optimal set of inputs is, therefore, obtained for each price.

The second decision model assumes the producer uses knowledge of the SO. Three phases of the SO are examined: warm (or El Niño), cold, and other (Kiladis and Diaz 1989). Texas generally experiences wetter, cooler weather during a warm phase and drier, hotter weather during a cold phase than the average. Current published literature states consistent weather patterns are experienced during the October to March–April period (Ropelewski and Halpert, 1986, 1987, 1989). Emerging evidence suggests these patterns may extend longer into the growing season (Sittle 1994). As such, each cropping year is classified as a cold, warm, or other phase on the SO based on the preceding year, because of the timing of the consistent weather pattern and the time period when sorghum is grown. In this model, for each price three sets of optimal inputs are obtained, one for each phase.

The economic decision model for producers without SO information is

$$E(\pi) = \max_{n,s,d,c} \frac{1}{m} \sum_{j=1}^{m} \Big[py_{ij}(n, s, d, c) - r_1 n - r_2 s - r_3 y_{ij}(n, s, d, c) \Big], \qquad (1)$$

where $E(\pi)$ is the expected net returns, m is the number of weather years, p is expected price in dollars ($) per kilogram (kg), y_{ij} is yield per hectare (ha) associated with site i and year j, n is applied nitrogen in kg ha^{-1}, s is seeding density in seeds ha^{-1}, d is planting date, c is cultivar planted, r_1 is nitrogen cost in ($ kg^{-1}), r_2 is seed costs in $ seed^{-1}, and r_3 is harvest costs in ($ kg^{-1}). For each expected price and site an input combination that maximizes expected net returns is determined. Associated with each optimum input combination is an expected yield. The expected yield for site i and a given price is

$$Y^e_{ip} = \frac{1}{m}\sum_{j=1}^{m} y_{ij}(n^*, s^*, d^*, c^*|p), \tag{2}$$

where the asterisks denote the optimal input combination. Aggregate production for a given price without SO forecast scenario is

$$A|p = \sum_{i=1}^{18} Y^e_{ip}h_i, \tag{3}$$

where $A|p$ is the expected aggregate production given price, p, and h_i is the number of hectares site i represents.

When the SO information is used, the decision model is modified to

$$E(\pi) = \sum_{q=1}^{3} \frac{1}{m_q}\max \sum_{j=1}^{m_q} [py_{ij}(n, s, d, c) - r_1 n - r_2 s - r_3 y_{ij}(n, s, d, c)], \tag{4}$$

where all variables are as previously defined and q represents the three possible SO phases, m_q represents the number of years associated with SO event q, and j represents the years associated with the appropriate SO event. Hence, the same calculations are used to obtain the optimal net returns for each subset of years identified with a specific SO phase. It must be stressed that, with SO information, optimal inputs and associated yields are obtained for each of the three subsets of years (ENSO, cold, and other) for each price. The occurrence of each year within a subset is assumed to be equally likely.

Expected yield for site i, SO event q, and a given price is

$$Y^e_{qip} = \frac{1}{m_q}\sum_{j=1}^{m_q} y_{ij}(n^*_q, s^*_q, d^*_q, c^*_q|p), \tag{5}$$

where the subscript on the optimal inputs denotes the different SO events. Aggregate production becomes

$$A_{so}|p = \sum_{q=1}^{3}\sum_{i=1}^{18} z_q Y^e_{qip}h_i, \tag{6}$$

where $A_{so}|p$ is aggregate production for a given price and z_q is the probability of the qth phase occurring.

Obtaining $(A|p)$ and $(A_{so}|p)$ for the various prices gives the expected aggregate sorghum supply curve. In addition to the aggregated supply curves, aggregate results are also presented for aggregate costs, net returns, nitrogen use, and planted hectares. These variables are aggregated by weighting the variable by hectares represented by each site and the probability of each SO event. The procedure used corresponds to the procedure used in obtaining the aggregate supply curves with the appropriate redefinition of the variables; therefore, the procedure is not presented here.

b. Biophysical simulation model and study sites

SORNIT, a modified version of SORKAM (Rosenthal et al. 1989), is used to provide the basis for the sorghum supply curves. The modifications, based on Kissel et al.'s (1975) research, allow SORNIT to simulate sorghum yields with differing nitrogen levels. Previous verifications of SORKAM indicate a close correlation between simulated yields and research yields. In one such study, SORKAM achieved an R^2 of 0.84 between simulated yields and research trial sorghum yields (Rosenthal and Gerik 1990). In addition, SORNIT is modified to account for the impact of the SO phases on preseason soil moisture.

Six of the 12 extension districts in Texas are selected for inclusion in the study (Fig. 1). To be selected, a district must historically account for at least 5% of Texas's sorghum production during 1989–92. The six districts selected historically produce approximately 78% of the total sorghum grown in Texas. Within each selected district, three representative sites are used to simulate sorghum production (Fig. 1; Table 1).

In Texas, higher precipitation levels are found along the Gulf Coast than elsewhere. Precipitation levels and average temperature decrease as one moves from the Texas Gulf Coast plains to the west and northern interior of the state (Rosenthal and Gerik 1990). Because of this precipitation pattern, an attempt is made to select sites in each district in a northwest diagonal pattern (Fig. 1). The quality of the meteorological data and/or the concentration of sorghum producing counties within a district did not, however, always allow for this diagonal pattern.

Daily weather data for 43 yr, 1950–92, are used whenever possible.[1] Missing data and the fact many meteorology stations did not become operational until the early 1960s forced fewer years to be used for some sites (Table 1). Further, evapotranspiration rates are not uniform across the state because of differences in altitude,

[1] Years classified as other SO events are 1951, 1953, 1956, 1957, 1959, 1960, 1961, 1962, 1963, 1967, 1968, 1969, 1972, 1975, 1978, 1979, 1980, 1981, 1982, 1984, 1985, 1986, 1988, 1990, and 1991, which compose 58% of the years used in this study. Warm events composed 26% of the years. Years classified as warm are 1952, 1954, 1958, 1964, 1966, 1970, 1973, 1977, 1983, 1987, and 1992. Finally, cold events composed 16% of the years. Cold event years are 1950, 1955, 1971, 1974, 1976, and 1989. For sites with less than 43 yr of data, the classification of events remains the same, but the probability of occurance is altered.

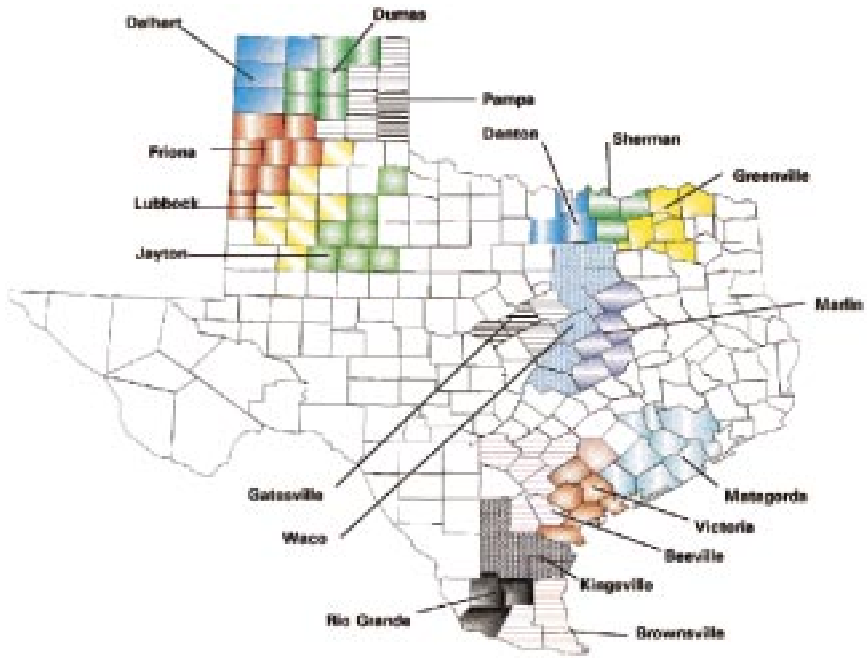

FIG. 1. Sorghum-producting districts represented in the study; names represent the site of the meteorological stations used in the simulation of sorghum yields.

TABLE 1. Characteristics of the sorghum production simulation sites.

Site	Soil type	Elev (m)	Lat (°)	Years with weather data	Ha (1000s)
Amarillo District					
Dalhart	Gruver	1300	36	1950–92	19.56
Dumas	Sherm	1215	35	1959–92	26.28
Pampa	Pullman	1080	35	1952–53, 1955–92	26.90
Lubbock District					
Friona	Olton	1330	34	1963–92	105.90
Lubbock	Olton	1080	33	1950–92	97.00
Jayton	Olton	668	33	1963–92	7.40
Dallas District					
Denton	Denton	210	33	1950–63, 1965–92	32.30
Greenville	Crockett	200	33	1950–92	18.30
Sherman	Houston	235	33	1950–92	48.00
Stephenville District					
Waco	Houston	165	31	1950–57, 1960–92	101.50
Gatesville	Denton	280	31	1950–92	10.30
Marlin	Wilson	120	31	1950–92	31.20
Corpus Christi District					
Beeville	Goliad	80	28	1950–92	54.70
Victoria	Lake Charles	33	28	1973–82, 1984–92	40.50
Matagorda	Lake Charles	3	28	1950–92	68.40
Weslaco District					
Brownsville	Harlingen	6	25	1950–92	81.60
Rio Grande	Hidalgo	58	26	1950–92	51.20
Kingsville	Orelia	22	27	1950–92	140.30

TABLE 2. Daily irradiance parameters by district (Langley's).

District	Daily irradiance: Dry day Average	Dry day Amplitude	Wet day Average	Wet day Amplitude
Amarillo	485	207	330	207
Lubbock	490	200	330	200
Dallas	460	180	280	180
Stephenville	465	175	290	175
Corpus Christi	465	167	282	167
Weslaco	470	170	287	170

solar radiation, soil characteristics, and wind conditions. Average annual rates range from 1600 to 2000 mm. Elevation increases from sea level on the Texas Gulf Coast plains to over 1000 m above sea level in the northern regions of the state. Finally, the state encompasses 25°–36°N lat. An attempt was made to account for these varying meteorological and physical characteristics. The daily irradiance patterns for each district are presented in Table 2. These patterns are used in the following equations to calculate daily irradiance (SOLRAD):

$$\mathrm{SOLRAD} = \mathrm{RDDM} + \mathrm{RDDA} \cdot \sin\left[\frac{2\pi}{365(D - 82.2)}\right],$$

or

$$\mathrm{SOLRAD} = \mathrm{RWDM} + \mathrm{RDDA} \cdot \sin\left[\frac{2\pi}{365(D - 82.2)}\right], \quad (7)$$

where RDDM and RWDM are the annual irradiance averages for dry and wet days, RDDA is annual amplitude, and D is the Julian day (Richardson and Wright 1984).

Whenever possible, soil type for each site is obtained from the *General Soils Map of Texas*, whereas soil profiles are based on the Texas state soil interpretation records (Godfrey et al. 1973). The soil parameters are selected by determining the most common soil types in the area represented by a meteorological site. From that set of soil types, the most common soil type suitable for sorghum production is selected (Table 1).

The highest clay percentage recorded for each horizon in the soil profiles is used to provide a measure for soil consistency. Not all soil interpretation sheets contained moisture bulk density information. Sensitivity analysis on potential moisture bulk density numbers indicated assumed bulk density numbers had little impact on yield. Consequently, an approximation by soil layer bulk density is used whenever a bulk density value was not available.

Average hectares over the years 1991–93 planted to dryland sorghum in each selected extension district is used as a representation of the hectares planted to sorghum (Texas Agricultural Statistics Service 1991, 1993). Sorghum-producing counties in each district are associated with one of three weather stations in that district. Criteria used in linking the county to the weather station sites are proximity to the site, physical characteristics (soil, elevation, latitude) of the county, and the northwest diagonal precipitation pattern.

c. *Management practices and economic data*

The representative production unit is assumed to be 1 ha cropped either continuously or fallowed. Continuous cropping is assumed when the expected annual precipitation level and evapotranspiration rate allows sorghum to be produced economically on an annual basis. Dallas, Stephenville, and Corpus Christi Districts are assumed to be continuously cropped, whereas Amarillo, Lubbock, and Weslaco Districts are assumed to be in a crop–fallow rotation. Such an assumption is consistent with historical cropping patterns for dryland sorghum. Continuous versus fallow cropping impacts preseason soil moisture values.

Three sorghum cultivars, early, medium, and late maturing, are included. The early cultivar matures approximately 95 days after planting with less than 2250 accumulated heat units. Approximately 95–105 days are necessary for the medium maturing cultivar to reach maturity. The medium maturing cultivar requires 2250–2430 accumulated heat units. More than 2430 heat units and approximately 105 days are needed for the late maturing cultivar to reach maturity (Rosenthal and Gerik 1990). Three planting densities, 112 500, 141 250, and 202 500 seeds ha^{-1}, are included.

Nitrogen fertilizer application rates are based on Kissel et al. (1975) and expert opinion (Coffman 1994, personal communication). Eight nitrogen rates examined are 80, 90, 100, 110, 120, 130, 140, and 150 kg ha^{-1}. Input costs used are nitrogen \$0.549 kg^{-1}, seed cost of \$0.0009 seed^{-1}, and harvesting costs of \$0.015 kg^{-1} of sorghum output (Mjelde et al. 1995). Planting dates vary by district because of climate differences. Three planting dates are defined for each district to represent early, normal, and late planting dates.

The range of prices for Texas sorghum are based on the yearly average Texas sorghum prices for 1972–92 (Texas Department of Agriculture–USDA 1993). To obtain three of the expected prices, prices from these 21 years are ranked from the highest to the lowest. The average of the lowest third, middle third, and highest third of the ranked prices gives three of the expected prices used. In addition, the lowest and highest price recorded of the 21 years are arbitrarily used to give a range of five prices. The expected prices used are \$0.06, 0.072, 0.0895, 0.106, and 0.12 kg^{-1}.

3. Results

a. *Generalities*

By design, optimal input combinations for producers not using SO information vary only by expected price.

TABLE 3. Lubbock District, Jayton site, sorghum supply with information concerning the Southern Oscillation by event and price.

Price ($ kg^{-1})	Input set*	Yield (kg ha^{-1}) Mean	Yield (kg ha^{-1}) Std dev	Net return ($ ha^{-1}) Mean	Net return ($ ha^{-1}) Std dev
		Other SO event			
0.0600	1111	3903	2080	30.98	93.60
0.0720	1311	4118	2132	78.55	121.52
0.0895	1411	4200	2153	151.00	160.39
0.1060	1511	4227	2171	221.50	197.51
0.1200	1511	4227	2171	280.88	227.90
		Cold SO event			
0.0600	1231	2904	1027	−19.99	46.21
0.0720	1431	3125	1027	16.49	58.52
0.0895	1531	3207	1027	71.82	76.49
0.1060	1631	3271	1027	125.02	93.43
0.1200	1631	3271	1027	170.80	107.81
		Warm SO event			
0.0600	1111	3976	2631	33.73	118.38
0.0720	1311	4185	2694	82.40	153.58
0.0895	1411	4207	2371	156.54	176.65
0.1060	1511	4340	2946	227.80	217.22
0.1200	1511	4340	3171	288.56	284.18

* Digit 1: Cultivar type
level 1 = early maturing,
level 2 = medium maturing, and
level 3 = late maturing.

Digit 2: Nitrogen rate
level 1 = 80 kg ha^{-1},
level 2 = 90 kg ha^{-1},
level 3 = 100 kg ha^{-1},
level 4 = 110 kg ha^{-1},
level 5 = 120 kg ha^{-1},
level 6 = 130 kg ha^{-1},
level 7 = 140 kg ha^{-1}, and
level 8 = 150 kg ha^{-1}.

Digit 3: Planting date
level 1 = 04/20,
level 2 = 05/30, and
level 3 = 07/10.

Digit 4: Plant density
level 1 = 112 500 ha^{-1},
level 2 = 141 250 ha^{-1}, and
level 3 = 202 500 ha^{-1}.

TABLE 4. Lubbock District, Jayton site, sorghum supply without information concerning the Southern Oscillation by event and price.

Price (% kg^{-1})	Input set*	Yield (kg ha^{-1}) Mean	Yield (kg ha^{-1}) Std dev	Net return ($ ha^{-1}) Mean	Net return ($ ha^{-1}) Std dev
		Other SO event			
0.0600	1111	3903	2080	30.48	93.60
0.0720	1511	4227	2171	73.80	123.72
0.0895	1511	4227	2171	147.77	161.70
0.1060	1511	4227	2171	217.51	197.51
0.1200	1511	4227	2171	276.68	227.90
		Cold SO Event			
0.0600	1111	1357	1478	−84.11	66.50
0.0720	1511	1605	1584	−75.62	90.28
0.0895	1511	1605	1584	−47.53	117.99
0.1060	1511	1605	1584	−21.04	144.12
0.1200	1511	1605	1584	1.44	166.30
		Warm SO event			
0.0600	1111	3976	2631	33.73	118.38
0.0720	1511	4340	2726	80.24	155.40
0.0895	1511	4340	2726	156.19	203.11
0.1060	1511	4340	2726	227.80	248.09
0.1200	1511	4340	2726	288.56	286.26

* See Table 3 for explanation of the input set.

When SO information is used, optimal input combinations vary by price and SO phase. The changes in optimal input combinations in response to the SO phase indicates producers have the flexibility to respond to SO information. Further as expected, producers incorporating SO information into their production process increased their expected net returns. This increase in net returns ranged from pennies to $90 ha^{-1} depending on the site, SO phase, and expected price. No clear pattern is observed when comparing the standard deviations of yields or net returns between the with and without SO information. Use of SO information does not appear to reduce the standard deviation of either expected average yield or net return.

Applied nitrogen level and planting date are the inputs most impacted by the use of SO information. In only one case does using the SO information change the optimal cultivar. Seed density is not impacted by the use of SO information. Changes in production also vary by site and SO information. This is not surprising since sorghum compensates by increasing or decreasing the number of tillers it produces based on the climate condition in which it is growing. At some sites, knowledge of the SO phases reduces expected production from the without knowledge production level. For other sites the opposite is true; expected production increases when SO information is incorporated into the production process.

Nitrogen use tends to decline with the use of SO information. Optimum input levels of nitrogen with knowledge are lower for many of the events and prices. Nitrogen use tends to converge to the without SO knowledge rates at the higher prices. Planting dates varied in response to knowledge of SO events. No clear pattern is observed with regard to planting dates.

b. Selected site results

As an example of the site results, consider the Jayton site (Tables 3 and 4). In Table 3, optimal input combinations may vary by SO event, because of the use of SO information. Although broken into the three events in Table 4, the reader should recall by design when SO information is not used, the optimal input set does not vary by SO event. The breakdown in Table 4 is for comparison purposes on expected yields and returns. This site illustrates several different ways SO information impacts the production decision process. Without information, the optimal input set is to plant an early maturing cultivar type and plant on 20 April using 112 500 seeds ha^{-1}. These decisions remain optimal regardless of price. At the lowest price, the optimal nitrogen application rate is 80 kg ha^{-1}, whereas for all the remaining prices the optimal nitrogen rate is 120 kg ha^{-1} (Table 4). Several ways in which decisions are changed using SO information are illustrated when comparing Tables 3 and 4.

First, consider the lowest sorghum price, \$0.600 kg^{-1}. At this price, the use of SO for the other and warm events does not change the optimal decisions. Without changes in the decision set, the mean yield and net returns for these events are the same between the with and without SO information cases. For the cold event, the optimal nitrogen application rate increases and the optimal planting date is later. This example shows that the use of SO information may cause an increase in costs (increase in nitrogen use and increase in harvest costs), which increases mean yield. For such a change, the increase in costs must be smaller than the increase in revenue caused by increased yields. During cold events, in both the with and without SO information cases, the optimal input sets results in negative expected net returns. The use of SO information, however, allows the producer to minimize losses. At prices between \$0.072 and 0.106 kg^{-1} the use of SO information turns a loss into a profit.

Next consider, a sorghum price of \$0.0895 kg^{-1}. For both the other and warm event, the use of SO information causes a decrease in the optimal nitrogen application rate (120 to 110 kg ha^{-1}). In these instances the use of SO information causes a decrease in costs by using less nitrogen. Using less nitrogen in turn decreases yields, which decreases revenues and harvest costs. This is an example of the decrease in costs outweighing the decrease in revenue. For the cold event, the optimal nitrogen level is the same regardless of the use of SO information. The optimal planting date is, however, later. Here, planting costs are the same between the use and nonuse of SO information as no monetary cost is associated with changing planting date. The change in planting date increases expected yield, which increases revenues net of harvesting costs. This is an example of no change in planting costs, but planting at the optimal time leading to increase in net revenues.

For all sites, results are similar in that the use of SO information allowed the producer to adjust input usage to increase net revenues. The increase in net revenues is caused either by lowering costs through lower input usage and/or increasing yields. In the majority of situations modeled, the use of SO information allowed the producer to lower the nitrogen application rate for at least one of the three SO events. Further site-specific results are discussed in Hill (1995).

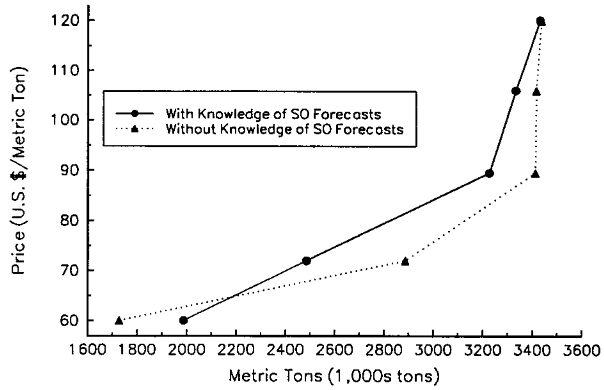

FIG. 2. Texas aggregate supply curves weighted by event and hectares, scenario one.

c. Aggregate supply curves

Aggregate supply curves are developed under two different scenarios. In scenario one, it is assumed producers do not produce when expected net returns are negative. Production is not allowed for the with SO information case when negative net returns are expected for specific events and a given price. Without SO information, producers do not produce if the overall net returns are negative for a given price. In scenario two, it is assumed the producers produce even when expected net returns are negative. Producers may produce when expected net returns are negative because of some institutional factors such as government programs, financial agreements, lack of complete confidence in the quality of the SO information, etc. The input combinations that generate the highest expected net returns are used to obtain expected yields.

Under scenario one, the with SO information expected aggregate sorghum supply curve (Fig. 2) shifts to the right relative to the without knowledge curve at the lowest price. Information concerning the SO phase results in an increase in production at the lowest price for many sites. Producers without SO information cannot separate out the individual phases; hence, they do not have the flexibility to tailor their input sets to specific events. Producers without SO information must choose an input strategy that is the most profitable over all phases. For many sites this produces an expected negative net return at lower prices. Under scenario one, producers cease production at the lowest price at many sites. The with SO information producers continue to produce in the phases that have a positive net return, causing the shift to the right by the with SO information supply curve at the lower price.

At higher prices, the expected aggregate with SO information supply curve shifts to the left of the without information curve. With SO information production declines for SO phases that have reduced precipitation relative to the without information production. This reduction outweighs any increases in production during

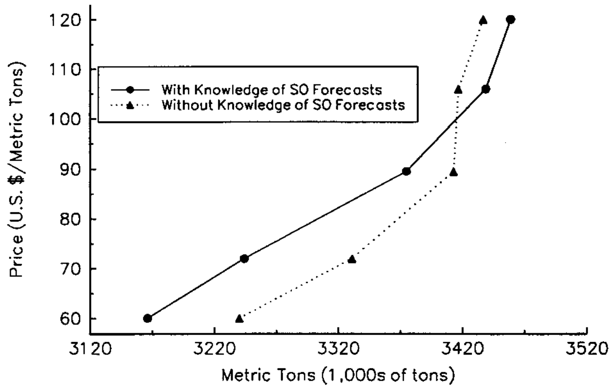

FIG. 3. Texas aggregate supply curves weighted by event and hectares, scenario two.

events that have increased precipitation. At higher prices the two curves converge. The increased marginal value of the commodity at the higher prices is diminishing the value of SO phase information. Percentage changes in aggregate production range from −13.9% to 15% depending on price.

Under scenario two at the lower prices, the with SO information curve shifts to the left of the without information curve (Fig. 3). The with SO information supply curve shifts to the left, because higher input levels are being used by the without information producers. With SO information, producers' expected negative net returns are less negative because of reduced input usage.

At the higher prices, the with SO information supply curve shifts slightly to the right of the without information curve. In scenario one, the with SO information producer ceases production when expected net returns for a specific phase and price are negative. In scenario two, this assumption is relaxed, which allows the with SO information production to increase by including sites and events that had negative net returns. The result is with SO information production shifts to the left of the without SO information production at lower prices and to the right at higher prices. Percentage changes in production range from −2.6% to 0.6% again depending on price. Note, the *x* axis ranges differ between the two figures. Differences in the axis can give an exaggerated impression of the magnitude of the shifts caused by the use of SO information, but are necessary because of the assumptions associated with each scenario.

Between the two scenarios, the with SO information supply curves differ at all prices. The without SO information curves differ only at the two lower prices. At the three higher prices, the without SO information curves are identical.

d. Expected planted hectares

A total of 961 340 ha are represented in the aggregate model. Under scenario two, all hectares are assumed planted. Recall however, the following assumption is made for scenario one: if the producers' expected net returns are negative for a given price and climate event (with SO information only), the producer will not plant. When producers do not use SO information, at the lowest two prices, hectares are taken out of production. At a price of $0.060 kg^{-1} expected (overall all years) planted hectares is only 363 976 ha, whereas at a price of $0.072 kg^{-1} expected planted hectares is 782 740. At the highest three prices, 961 340 ha are always planted.

When SO information is used, the producers can adjust hectares planted not only in response to price, but also in response to the SO event. Under this scenario, the expected planted hectares vary by price and never reach the total possible number of hectares. Expected (weighted by SO event) planted hectares for the five prices (lowest to highest) are 467 453, 586 785, 876 485, 905 559, and 946 049. At the lowest price, the use of SO information increases the number of hectares planted (467 453 vs 363 976). Information concerning which SO event is occurring allows the producer to plant during those events that have positive net returns, whereas producers without SO information only plant when it is profitable over all years. For all other prices, the use of SO information reduces the amount of expected hectares planted. Here if it is profitable over all years to plant (without SO information), use of SO information allows the producer to not plant in that subset of years it is not profitable.

e. Expected nitrogen use

Besides planted acreage, nitrogen is the input with the most influence on total production. The expected aggregate use of nitrogen declines with the use of SO information over the without knowledge scenario at all prices (Table 5). Under scenario one, the decline in aggregate nitrogen use is greatest. At lower prices, where more hectares are removed because of negative expected returns, the decline in aggregate nitrogen use is highest. At the lowest price, there is an estimated decline in aggregate nitrogen use of 27% from the without SO information case. The decline in nitrogen use is less pronounced at the higher prices. The SO information reduces nitrogen use per hectare, but relatively few hectares are actually removed from production at the higher prices. Per hectare use of nitrogen also decreases with the use of SO information for all prices except for a price of $0.072 ha^{-1} in scenario one. Changes in nitrogen use at the lower prices in scenario one are attributed to the use of SO information and changes in hectares planted. At the lowest price, only the best land is planted because of the potential for negative net returns.

Reductions in nitrogen use are less dramatic for scenario two (Table 5). The primary reason for this is the hectares removed from production in scenario one remain in production in this scenario. Consequently, reductions in nitrogen use are strictly caused by the more

TABLE 5. Expected aggregate nitrogen use at different sorghum prices based on the use of SO information.

Prices ($ kg^{-1})	With SO: Aggregate (1000s metric tons)	With SO: (kg ha^{-1})	Without SO: Aggregate (1000s metric tons)	Without SO: (kg ha^{-1})	Percentage change in aggregate use (%)
Scenario one					
0.0600	38	81	52	143	−26.9
0.0720	68	116	84	107	−19.0
0.0895	97	111	116	121	−16.4
0.1060	108	119	117	122	−7.7
0.1200	115	122	121	126	−5.0
Scenario two					
0.0600	80	83	93	97	−14.0
0.0720	88	92	105	109	−16.2
0.0895	103	107	116	121	−11.2
0.1060	111	115	117	122	−5.1
0.1200	116	121	121	126	−4.1

efficient use of nitrogen. Even so, expected nitrogen use declines between 4.1% and 14% depending on price.

f. Expected costs

Changes in hectares planted, applied nitrogen rate, and expected yields all impact the expected cost of production. Expected aggregate costs associated with the different prices and scenarios are presented in Table 6. Under scenario one and a price of \$0.06 kg^{-1} the use of SO information increases aggregate costs 14.4% (\$98 482 vs \$86 072). This increase in aggregate costs is attributed to the increase in hectares planted. At all other prices, the use of SO information decreases aggregate costs. This result corresponds to the decrease in planted hectares and nitrogen use previously discussed. Decreases in aggregate costs range from 0.6% to 26.5%. On a cost per metric ton produced, the use of SO information always reduces production costs. This reduction in costs ranges from \$0.29 to \$8.63 metric ton^{-1}. Changing production costs not only increases net returns of the producers, these changes indicate less inputs are bought which will impact input supplies and rural communities. These impacts are, however, beyond the scope of this study.

g. Expected net returns

For any expected price, the previously discussed changes in yields and costs impact aggregate expected net returns (Table 7). These changes in net returns give the value of the use of SO information to sorghum producers in Texas. Two caveats to the use of all the expected changes in this study are warranted. First, the aggregate values are weighted by hectares and the probability of SO events, therefore, by design do not represent any individual producer. Second, the results are for a given expected price, that is, any price changes caused by the use of SO information are not incorporated.

In scenario one, the use of SO information increases producers net returns between 3.3% and 14.8% depending on the price. For scenario two, the increases in net returns are between 3.1% and 132.9% (in absolute value). The use of SO information is inherently risky. The SO information classifies a subset of years, but

TABLE 6. Expected aggregate production costs at different sorghum prices based on the use of SO information.

Sorghum prices ($ kg^{-1})	With SO: Aggregate costs ($1000s)	With SO: Cost ($ metric ton^{-1})	Without SO: Aggregate costs ($1000s)	Without SO: Cost ($ metric ton^{-1})	Percent aggregate change (%)
Scenario one					
0.0600	98 482	49.54	86 072	49.83	14.4
0.0720	125 109	50.33	170 229	58.96	−26.5
0.0895	188 551	58.43	211 599	62.00	−10.9
0.1060	199 246	59.74	212 028	62.05	−6.0
0.1200	210 270	61.26	214 039	62.27	−1.8
Scenario two					
0.0600	188 971	59.69	196 956	60.79	−4.1
0.0720	194 566	59.98	206 490	61.99	−5.8
0.0895	204 332	60.54	211 599	62.00	−3.4
0.1060	209 890	61.03	212 028	62.05	−1.0
0.1200	212 750	61.51	214 039	62.27	−0.6

TABLE 7. Expected aggregate net returns at different sorghum prices based on the use of SO information.

Sorghum prices ($ kg^{-1})	With SO: Aggregate net returns ($1000s)	With SO: Net returns (metric ton)$^{-1}$ ($ ton^{-1})	Without SO: Aggregate net returns ($1000s)	Without SO: Net returns (metric ton)$^{-1}$ ($ ton^{-1})	Percent aggregate change (%)
Scenario one					
0.0600	20 812	10.51	18 127	10.50	14.8
0.0720	46 841	18.84	38 835	13.45	20.6
0.0895	99 727	30.90	92 253	27.02	8.1
0.1060	154 723	46.39	148 302	43.40	4.3
0.1200	202 693	59.06	196 258	57.10	3.3
Scenario two					
0.0600	1019	0.32	−3096	−0.95	132.9*
0.0720	39 519	12.18	33 415	10.03	18.3
0.0895	97 661	29.94	92 253	27.02	5.9
0.1060	153 869	44.74	148 302	43.40	3.8
0.1200	202 333	58.49	196 258	57.10	3.1

* Percentage change calculation in absolute value term.

within the subset there remains a wide range of climatic conditions. Even with this imperfect climate knowledge, it appears producers would benefit from the use of SO information if price changes do not occur. Because the supply curves based on SO information shift both to the left and right of the without SO information supply curve, the impact on price is difficult to ascertain. But the leftward shift, which is the most prevalent, indicates an increase in price caused by the use of SO information ceteris paribus for all regions may occur if the Texas sorghum sector is large enough to affect the total sorghum market.

4. Conclusions and discussion

Several implications can be drawn from the results. First, it appears that the use of SO information will influence the aggregate supply curve and other economic variables, which in turn will impact the agricultural sector. The impact on consumer and producer welfare depends on factors such as the expected price, the elasticities of demand and supply, and changes in costs. Expected price is important because for a given price either a rightward or a leftward shift of the supply curve is noted when SO information is used. Because the SO signal varies in magnitude across the world, international trade balances may be impacted. The effect of the SO can be the same or the opposite of that observed in Texas for each event in other regions of the world. This is especially true because it appears the SO's influence on climate in other agricultural producing areas is different than its impact on Texas climate. How SO information changes consuming and producing nations' comparative advantages requires further study. Because the current study treats sorghum price as exogenous, no attempt is made to determine the effect on society's welfare or international trade.

Use of SO information will influence resource use. In this study, two resources with potential environmental impacts, nitrogen use and land use patterns, are influenced. Land use patterns in this study are only influenced by the decision to plant or not plant, but the use of substitute crops may have an even larger impact. Depending on the site and expected price, nitrogen use either increased or decreased. Overall, aggregate nitrogen use decreased with the percentage decrease depending on assumptions concerning land use patterns and expected price. The SO information does, however, allow for the more efficient use of resources.

Several authors have noted the use of climate forecasts can be viewed as a technological advance with a rightward shift of the supply curve (Greenberg 1976; Mjelde et al. 1989). Improved climate forecasts are clearly an advance for the science of meteorology. The question is raised, do improvements in forecasts represent an improvement in technical efficiency? Strictly speaking, improvements in technical efficiency change the production function by increasing the productivity of inputs for a good without reducing the output of another good (Nicholson 1992). The shift left by the aggregate supply curves is unexpected if one views the SO forecasts as strictly an improvement in technical efficiency. Increases in technical efficiency mean a unit of input is able to produce more output. Therefore, this causes the marginal value product to increase. The increase in the marginal value product should shift the supply curve to the right over the range of relevant prices.

The SO forecast information does not appear to change the technological relationship between inputs and outputs. It does appear to allow the decision maker to select the most appropriate input levels for the expected climatic event. Yields per hectare do not increase for the same amount of nitrogen for a given year regardless of the SO information. For the preceding reasons it is likely this improved information is not a technological change in the classic sense. Because it improves the producers' net returns, it raises the possibility that it may be a technological change in that it produces a more efficient use of resources.

Other authors note the use of climate forecasts may be used as an input substitute for other more expensive inputs (Lamb 1979, 1981; Sonka et al. 1982). It is difficult to determine if the improved SO forecasts are a form of input substitution. Optimal applied nitrogen level decreased or increased depending on the site, SO information, and price. The inputs are not reduced for all sites, because of the inclusion of SO information in the decision process. It appears that the information is not acting as a substitute for other inputs such as nitrogen at the individual site. At the aggregate level, expected nitrogen used and costs decreased, which indicates a substitution effect.

A more appropriate argument is improvements in climate information allow the decision maker to identify the most efficient input combination for an expected climatic event. The improved climate information allows the producer to identify the most efficient input combinations. Whether this is a form of technology shift or a form of input substitution is not clear. Results suggest the use of SO information has characteristics of both technological change and input substitution. What is true is that using SO information provides a method to use inputs more efficiently.

This study does not take into account a variety of factors such as the possibility of crop substitution and interactions between SO phases and pests, diseases, and weed competition. In addition, irrigation impacts are not examined. Nonetheless, the study does provide some interesting insights into how this emerging technology may influence the agricultural sector. The next step is to provide an endogenization of expected price through a modeling of the demand and supply aspects of the agricultural sector. To properly conduct such an analysis, the methodology used in this study needs to be expanded to other crops because of the possibility of substitution in the agricultural sector. Such an undertaking is no small task and must include price expectation relationships of not only demand and supply, but an expectation mechanism relating climate information to prices.

Acknowledgments. This study was partially funded by National Science Foundation Grants ATM 92-44870 and INT 91-96196, Department of Commerce National Oceanic and Atmospheric Administration Grants NA36GP0383 and NA56GP0266, the Cooperative Institute for Mesoscale Meteorological Studies at the University of Oklahoma, and the Texas Agricultural Experiment Station, Project 3914.

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