Improving El Niño Forecasting: The Potential Economic Benefits

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About This Publication

This publication reports on an ongoing pro gram of research and analysis to quantify the economic benefits of improved forecasts of ENSO (El Niño-Southern Oscillation) seasonal-to-interannual climate events. The project is under the direction of NOAA's Chief Economist. Quantifying economic benefits is a useful tool in setting research and operational priorities across the wide range of NOAA programs and activities as well gauging the social returns to the expenditure of public dollars. Because of the widespread attention to the 1997-99 El Niño/La Niña event, arguably the major climate event of the decade, special analyses of its economic consequences were undertaken and included here.

The project was undertaken with the encouragement of NOAA's Stan Wilson, Mel Briscoe (now at ONR), and Jim Baker, and Nic Flemming at the Southhampton Oceanography Centre, the UK. Funding was supplied from a pool of resources created by the NOAA's National Ocean Service (NOS), the National Weather Service (NWS), and the National Environmental Satellite, Data, and Information Service (NESDIS). Jerry Slaff provided all the layout and production.

This is an ongoing effort. Comments and suggestions for future directions are welcome.

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This publication is dedicated to our colleague, the late Peter Sassone, of the Georgia Institute of Technology.

Preface

Each year the impact of hurricanes and tornadoes take their toll of lives and of whole communities. Despite the billions of dollars in losses annually in the United States alone, those losses are still less today than they would have been a decade ago. That is because our ability to forecast climatic events has become increasingly more sophisticated and accurate. In forecasting hurricanes, for example, the lead time has become long enough to warn communities about the need for precautions in protecting their people and to alert them on whether or not they need to evacuate threatened areas.

Unlike these seasonal disruptions in weather, the El Niño Southern Oscillation is a climatic cycle that has longer term implications on weather patterns throughout the world. The 12- to 18-month cycling between warm states (El Niño) and cold states (La Niña) can alter temperatures and rains to such an extent that they significantly disrupt agriculture, commercial fishing, tourism and many diverse businesses and industries. Over the last decade, we have improved the forecasting of El Niño Southern Oscillation (ENSO) so that we can now predict these events and their expected climatic impacts on different regions with some 70 to 80 percent accuracy a year before they occur.

Such forecasts and potential improvements on them have powerful new economic implications that industry can turn to its advantage better than it has so far. The papers in *Improving El Niño Forecasting: The Economic Benefits* give different perspectives on just how by examining the impacts of seasonal climate variations, current forecasting capabilities, and the potential economic benefits of further improving them. They assess the economic impact of the 1997-98 El Niño, arguably the major climate event of this decade, and attempt to put a dollar amount on the benefits of improved El Niño forecasts.

In "Assessing the Economic Impacts of El Niño and the Benefits of Improved Forecasts," Rodney Weiher and Hauke Kite-Powell point out that nearly 15 percent of GDP originates in climate sensitive industries and that the economic impacts of the 1997-98 El Niño likely exceeded $10 billion, although, because of the many winners and losers, it is not clear whether the net effect was positive or negative. They provide snapshots of how producers and consumers were impacted by El Niño and how they can benefit from improved forecasts. In surveying a number of commercial sectors, the authors argue the cost effectiveness of stepping up public investment in U.S. capabilities for improving the acquisition of climatic data on which better modeling and ENSO forecasting will depend.

Thomas Teisberg's premise in "The Economic Value of an Improved ENSO Forecast" is that for climatic forecasts to have economic value, businesses must be able to make better decisions based on making use of them. He considers a number of situations - among them, the prevention of property damage, agriculture, space heating and cooling systems, hydroelectric management, construction and outdoor recreation - to assess how well they meet this criteria.

Agriculture is the most climate sensitive industry and climate is the primary determinant of agricultural productivity. In "'The Economic Consequences of El Niño and La Niña for Agriculture," Richard Adams, Chi Chang Chen, Bruce McCarl and Rodney Weiher present estimates of the impacts on U.S. agriculture of the 1997-98 El Niño and the 1998-99 La Niña; those losses range from $1.5 to $1.7 billion from El Niño and $2.2 to $6.5 billion from La Niña.

El Niño can be a big factor in how much it costs to heat homes and businesses. The "Effects of 1997-1998 El Niño on Natural Gas and Distillate Fuel Oil Costs" by Thomas Teisberg summarizes estimates of consumer fuel costs savings that resulted from the warmer temperatures which El Niño brought with it in 1997-98. According to Teisberg, the total cost savings from reduced use of natural gas in residential and commercial sectors and for total distillate fuel use added up to more than $2 billion. An accompanying case study by Richard Nichols of Minnegasco, a large natural gas distributor in Minnesota, evaluates the impact of the extremely warm El Niño temperatures—nearly 10 percent warmer than average—on decision-making within the company and suggests how business risks could be evaluated with better long-term forecasts.

"The Value of Improved ENSO Prediction to U.S. Agriculture" by Andrew Solow and a team of collaborators reports on the first systematic effort to estimate the economic value of more accurate El Niño predictions on U.S. agriculture. In broad terms, the economic effect of improved ENSO prediction is the same as a technological improvement that increases the supply of agricultural products. Recognizing the limitations of such empirical forecasting, the authors calculate the value to consumers and producers of improved forecast at $266 to $320 million annually. Put another way, if these future annual benefits are expressed in today's dollars and appropriately discounted, the value to the agricultural sector of a high skill ENSO prediction operating over 10 years is around $2 billion.

In "The Value of El Niño Forecasts in Agricultural Commodity Markets: The Case of U.S. Corn" Kevin McNew focuses on potential savings in the costs of stockpiling farm commodities with better climate forecasts. He concludes that with perfect predictions of El Niño events, U.S. corn stocks would decline by some 9 percent on average, about a $240 million benefit annually to farmers and consumers.

Richard Adams and his colleagues in "The Value of Improved ENSO Forecasts on Fisheries in the Pacific Northwest" assess the economic value of improved ocean and climatic forecasting on ocean fisheries, in particular, the environmentally sensitive but commercially small coho salmon fishery. Based on preliminary assessments, the authors employed two different models and estimate annual returns between $250,000 and $900,000 on the coho fishery, while pointing out better management actions that can be taken in the face of an accurate ENSO forecast.

Our ability to accurately forecast ENSO events is the result of investments in ocean observing systems and climate research. In the concluding paper, "Cost Benefit Analysis of TOGA [Tropical Ocean Global Atmosphere] and ENSO Observing System," the late Peter Sassone and Rodney Weiher summarize a cost-benefit analysis of the TOGA ocean observing program. Using benefits to US agriculture alone, and depending upon forecast accuracy and the degree to which farmers use the forecast, they report that these investments return at least 13 to 26 percent per annum, which is considerably above the minimum seven percent required for government investments in the U.S.

The summary papers in this volume all point to one conclusion: improvements in climatic forecasting of El Niño can have economic payoffs for businesses and the U.S. population. The overriding message is this: while we have improved our climate forecasting considerably over the last decade and have reaped social and economic advantages, we have the opportunity for making further improvements. With such improvements, the potential economic value to different sectors throughout our national economy could improve significantly as well.

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Assessing the Economic Impacts of El Niño and Benefits of Improved Forecasts

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Variations in climate from one year to the next can have significant economic conse quences. For example, the El Niño of 1997/98 brought a mild winter to the northern Midwest and greater than average rainfall to the Southwest and the west coast of the United States. As a result, U.S. energy consumers spent $2.2 billion less on oil and gas for heating than in an average year,[1] and losses in U.S. agricultural production cost producers and consumers about $3 billion.[2] Worldwide, effects associated with the El Niño/Southern Oscillation (ENSO) climate phenomenon appear to account for over 20 percent of commodity price inflation movements in recent years.[3] Today, ENSO events are well documented and, increasingly, predicted with accuracy. Both the events themselves, and more importantly their forecasts, are being used as an input to important economic decisions.

The magnitude of weather and climate effects on economic activity has led to a rapidly growing market for "weather hedges"—a form of insurance against economic losses from weather and climate swings. By some estimates, the market for weather hedges may reach $70-100 billion in a few years.[4] Hedges and insurance are one form of protection, but they do not eliminate losses from climate fluctuations: they merely spread the risk, and reduce a particular firm's exposure. To actually reduce the economic impact of climate fluctuations, we need better climate forecasts.

We are now able to forecast ENSO events one year in advance with about 70 percent accuracy. This is a big improvement over what was possible just ten years ago, but important gaps remain in the forecast of specific consequences. Take, for example, the 1997/98 El Niño—probably the most widely anticipated and publicized worldwide climate event ever. It followed historical El Niño patterns, but with some important variations. Historically, El Niño winters produce cool, wet conditions from the southern Plains eastward to Florida and mild weather in the northern Plains and New England. There is also some tendency for dryness in the Ohio Valley and over the northern Great Plains, and for enhanced storminess in California. The U.S. National Weather Service correctly forecast heavy winter precipitation across California and the southern Plains/Gulf Coast region at least six months ahead of time. The warmth across the northern half of the country was also correctly forecast, though it extended further southward than anticipated. While fall and winter forecasts were reasonably good, the quality of forecasts for spring was poor because a circulation pattern developed that did not conform to historical El Niño events.

From the country's perspective, some effects of climate fluctuations are more significant than others. For example, the reduced use of oil and gas for heating during the winter of 1997/98 produced benefits for consumers (lower expenditures) but resulted in costs for energy suppliers, who were unable to sell as much product as they expected. The net effect for the country is the balance of these consumer and producer effects; in this instance, it was probably a net positive. On the other hand, the $3 billion loss in agriculture is a true loss in consumer and producer surplus – the value consumers get from buying agricultural produce at lower costs and the profits producers make by growing it. Table 1 lists these and other economic activities that are affected by climate events (see Columns 2 and 4, page 6).

Among other effects, the 1997/98 El Niño contributed to winter floods in California that damaged strawberry and lettuce crops, a cool spring in Arizona that delayed cotton planting, and a drought in Texas that affected most crops. Using data on crop yields from past ENSO event years and economic models of the U.S. agricultural sector, it is possible to estimate the economic consequences of these effects. If the effects of the past winter's La Niña track those of the 1988 event, for instance, the economic losses in U.S. agriculture will be in the range of $2-6 billion.[2] The pattern of these events is not uniform, and some regions, such as the Southeast and Southwest, are affected more than others.

The economic effect on the U.S. economy as a whole from the 1997/98 El Niño is not known precisely; and it is not even clear whether the net effect was positive or negative. Collectively, climate-sensitive industries, such as agriculture, recreation, construction, energy distribution, and water supply management, account for nearly 15 percent of GDP. Based on examples such as those in Column 3 of Table 1, aggregate economic impacts of the recent El Niño were likely in excess of $10 billion. The important point, however, is that better forecasts can help turn climate events to advantage.

How can forecasts help? Climate forecasts are valuable if producers and consumers can use them to make decisions that improve the outcome of their economic activities (see Column 3 of Table 1). For example, farmers can use temperature and precipitation forecasts with lead times of six to 12 months to make decisions about what crops to plant. If their region is expected to be drier than usual during the coming growing season, farmers may choose to plant more drought-resistant varieties, and thereby improve crop yields. Similarly, energy distribution companies could increase stockpiles of heating oil and gas if the coming winter is forecast to be colder than usual, thereby avoiding shortfalls that are costly to both distributors and consumers. Even coat and apparel manufacturers are using forecasts with up to one-year lead times to anticipate demand for their merchandise—and buying weather insurance to cover potential losses.[5]

Benefits may also be realized in other industries that depend on weather, such as water reservoir management for hydroelectric power generation and irrigation, construction, and storm damage mitigation and repair. For example, there is evidence that extensive preparations by California homeowners, businesses, and emergency management officials in response to the ENSO forecast paid off handsomely in reduced storm damage. Property damage along the California coast was a hefty $500 million in the first three months of 1998, but this was much lower than the $1.8 billion losses recorded from the severe coastal storms in both 1995 and 1997.[6] Weather and climate forecasts are increasingly being relied upon in industries such as agribusiness, motor and rail freight, recreation, and, of course, air transportation.

Several recent studies have focused on how forecasts of climate events can be used in industries such as agriculture (see Column 5 of Table 1). One of these studies found that by incorporating NOAA's ENSO forecasts into planting decisions, farmers in the United States could increase agricultural output and produce benefits to the U.S. economy of up to $300 million per year, depending on the accuracy of the forecast.[7] Another study has estimated that the value to society of ENSO forecasts on corn storage decisions in certain years may be as high as $240 million—or one to two percent of the value of production.[8] Interestingly, the corn storage study suggests that in certain cases, the value to society of improving the forecast is greater when the forecast is more accurate to begin with.

Like agriculture, segments of the fishing industry can gain by incorporating climate forecasts into management and harvest decisions. For example, using ENSO forecasts in a small northwestern coho salmon fishery has been estimated to produce net benefits of nearly $1 million per year, nearly 10 percent of the landed value produced by this fishery.[9]

There are no quantitative estimates of the value of climate forecasts to the heating energy distribution business. Compared to agriculture, it is difficult to make year-by-year adjustments in oil and gas distribution because the energy business relies on expensive infrastructure and because the cost of running short in a cold winter is great for both suppliers and consumers. However, it is likely that suppliers could make economic use of climate forecasts by building additional stores when a colder winter is expected and by timing drawdowns to minimize storage-related costs. The resulting lower prices would benefit consumers as well.

When farmers and others make plans based on "average weather," disruptions in climate can lead to economic losses. The ability to forecast climate variations allows people to tailor their decisions and reduce these losses. A long-term strategy of following the climate forecasts should result in increased benefits to society. However, this requires confidence on the part of decision makers in the quality of the forecasts. By some measures, present ENSO prediction is about 70 percent accurate one year in advance, but the predictions of associated climate events are not yet perfect. For example, the 1997/98 El Niño was expected to bring a relatively wet fall and a dry spring to the Tennessee Valley Authority's reservoir recharge areas—but the opposite pattern materialized, in part because of nontypical circulation patterns. Further, in agriculture, changes in crop yields are only one factor determining economic consequences to farmers and consumers; local and international economic conditions also play an important role.

What is needed to produce better forecasts? In short: better models and better data. Climate models produce temperature and precipitation forecasts from data on ocean temperature, atmospheric pressure, and other factors. In the United States, the public and the private sectors share in the effort to produce and make use of climate forecasts. Several private weather forecasting companies produce tailored products for clients in many industries. These forecasters rely on base data and fundamental models provided by the government. This division of responsibility is sensible. The oceanic and atmospheric observations on which weather and climate forecasts depend are a classic public good, most efficiently provided by a public organization like NOAA.

Improving climate forecasts now will require some new investment in the public sector part of this system. The cost-effectiveness of earlier investments in ocean observation has been amply demonstrated. The buoys arrayed in the tropical Pacific to measure ocean temperature and other conditions are the basis for our ENSO predictions. Better ocean observations are on the critical path to improved forecasts; efforts are now underway to produce more extensive and consistent observation of ocean conditions through a Global Ocean Observing System (GOOS). And recently, the National Research Council called for better coordination among U.S. efforts to improve climate models. These initiatives are important if we are to continue to make progress in the age-old human endeavor to anticipate and guard against fluctuations in climate and weather.

Acknowledgments

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Table 1

	Column 1	Column 2	Column 3	Column 4	Column 5
economic activity	***economic scale of activity***	***effect of long term weather fluctuations***	***how forecasts can be used***	***effects of the 1997/98 ENSO event***	***estimates of forecast value (perfect forecast)***
Crop agriculture	$109 billion (1996 cash receipts, all U.S.)	temperature and rainfall affect crop yields	farmers can select crop varieties appropriate to expected temperature and rainfall conditions; distributors can reduce commodity storage if uncertainty about future yields is reduced	$3 billion losses to producers and consumers	$300 million/year for U.S. agriculture $240 million/year for corn storage industry
Fisheries	$3.5 billion (1996 landings, all U.S.)	water temperature and streamflow affect fish abundance and reproductive behavior	fishery managers can adjust harvesting to ensure adequate spawning	decreased output of fishmeal in South America	$1 million/year for one northwestern coho salmon fishery
Oil and gas distribution	$76 billion (1992 natural gas production and distribution) $7 billion (residential and commercial heating gas and fuel oil, average)	temperature affects demand for heating fuels	energy suppliers can adjust fuel stores and better time drawdown of stored fuel	$2 billion reduced expenditures for heating fuels due to mild winter	?
Water supply management	?	precipitation affects the amount of water entering reservoirs and the demand for irrigation	water supply managers can improve reservoir management by anticipating future inflows	fall precipitation was late, but spring flows tracked forecast	?
Storm damage mitigation and repair	$16.7 billion (1992 value of roofing/siding construction work)	storms (wind and precipitation) cause damage to buildings and other infrastructure	homeowners can take measures to minimize storm damage (preemptive repairs); municipalities can prepare for possible floods (clearing drainage canals, etc.)	$500 million in property damage in California $275 million FEMA obligations for storm and flooding damage sales of roofing material etc. up 20% in CA	?

Recreation	$100 billion (1992 hotels and recreational amusement centers)	temperature and snowfall affect winter sports conditions; rainfall affects other outdoor recreation	vacationers can improve their vacation experience by better planning their travel and sports activities	better than average recreational fishing in California, Florida, mid-Atlantic states	?
Construction	$528 billion (1992 construction industries)	temperature and precipitation affect whether construction can proceed	construction managers can better schedule projects	increased seasonal home construction in mid-Atlantic region; more working days for carpenters, painters, etc.	?

The Economic Value of an Improved ENSO Forecast

Thomas J. Teisberg

Abstract

For an improved ENSO forecast to have value, two conditions must be met. First, economic wealth or income must be affected by the weather, and second, it must be possible to make better economic decisions when a reliable ENSO forecast is available. This paper presents a brief discussion of a number of areas where these two conditions may be met. Of these, agricultural production may be the most important. Other areas where an improved forecast may have significant value are prevention of storm damage, natural gas storage, and management of hydroelectric facilities.

I. Introduction

In recent years, the National Oceanic and Atmospheric Administration (NOAA) has been able to make reliable forecasts of the weather phenomenon known as the El Niño Southern Oscillation (ENSO). ENSO has three states, known as El Niño, El Viejo (or La Niña), and Normal. US weather conditions over periods of several months are predictably different depending on which of these states exists. For example, during an El Niño state, winter weather tends to be warm in the Upper Midwest, and wet in the Southeast. NOAA has become proficient at predicting the ENSO state with several months leadtime.

Most people automatically assume that better weather information is a good thing and thus would have economic value.[1] The true situation is more complicated, however. For a better weather forecast to have economic value, two conditions must be met. First, weather must have an effect on economic wealth or income. Second, and more subtly, it must be possible to make better economic decisions when a better weather forecast is available. As the foregoing implies, to find situations where a better weather forecast would have economic value, one must identify situations where wealth or economic activities are affected by weather and in which it is possible to make better decisions if a reliable forecast is available.

II. Possible Effects of Weather on Economic Wealth or Activity

Economic wealth is affected by weather when there are storms strong enough to damage property.[2] Also, a number of economic activities are clearly affected by weather. Perhaps the must obvious such activity is agriculture, which is highly sensitive to both temperature and precipitation. In addition, space heating and cooling requirements obviously depend on outside temperatures. Perhaps less obviously, water management for power generation is sensitive to precipitation. Construction activities are more efficiently carried out when the weather is warmer and dryer. Some kinds of outdoor recreation, such as skiing,

[1]Better information should never be a bad thing, since information can always be ignored. However, there is a possible exception to this—the “ignorance is bliss” exception. For example, if you could learn the exact date of your death, but you could do nothing to change it, your enjoyment of what remains of your life might be diminished by knowledge of your date of death.

[2] Some storms are strong enough to present risks to human life. However, regular daily weather forecasts, rather than inter-annual ENSO forecasts, are relied on to avoid or reduce these risks.

may be more enjoyable and/or cheaper to provide when temperature and precipitation patterns are favorable.

III. Making Better Decisions With a Reliable Forecast

As noted above, for a forecast to have economic value, it must be true that better decisions can be made if a better weather forecast is available. The following sections discuss whether this condition is likely to be met in the situations noted above where weather affects economic wealth or economic activity.

A. Preventing Property Damage

There certainly appear to be situations where decisions that protect property from storm damage can be improved if a reliable ENSO forecast is available. On the U.S. West Coast, for example, El Niño frequently brings a great increase in winter precipitation. Prior to the winter of 1997-8, there were reports of heavy demand for the services of roofing contractors, as people repaired or replaced roofs in anticipation of predicted El Niño storms. This can be viewed as routine maintenance work that is accelerated because there is reason to think that winter storms will be particularly strong. The benefit of such accelerated maintenance is a reduction in the risk or extent of damage to the inside of structures due to leaking roofs during heavy winter storms.

B. Agriculture

In agriculture, there are many decisions that could be improved if a reliable weather forecast is available. Different crops have different water requirements, temperature sensitivities, and growing seasons. Thus, crop choice is a key decision that is sensitive to a weather forecast. In addition, for any given crop, there may be decisions about the timing of planting and harvesting and methods of fertilization and pest control that might be improved with a better weather forecast.

A recent study considered the value of improved weather forecasts for agriculture in the U.S.[3] This study focussed on decisions about what crops to plant. For a perfect ENSO forecast, the study found that the value of the forecast was on the order of $320 million per year or one to two percent of the total farm-gate value of crop production. For a forecast accuracy improvement from 60 percent to 80 percent, the value of the forecast improvement was estimated to be about $240 to $265 million.

C. Space Heating and Cooling

For space heating and cooling systems, the decisions that could be made better with a better weather forecast are less obvious. At the "downstream" consumption end of heating and cooling systems, most people simply set a thermostat that automatically makes "on the spot" fuel consumption decisions depending on weather conditions as they change. Somewhere in the fuel delivery system, however, people make decisions that determine the system's capacity to deliver fuel or energy. These decisions are a little different depending on whether the energy system is one supplying natural gas or petroleum.

Natural gas is primarily delivered by pipeline. Pipelines are costly to build, and once built will last for years. Thus, pipeline construction decisions will not be affected by one season's forecast of warmer or colder weather. As a result, the capacity of pipelines to deliver gas is strictly limited in the short run, and gas storage is used to deal with short run variations in the demand for gas.

In a typical gas system, there may be two kinds of storage—large scale storage of gas in underground sites such as salt domes, and much smaller scale storage of gas in the form of propane that can be added to natural gas. Typically, the propane storage is located very near to gas markets, and it is used to meet extreme peak winter gas demands over periods of days. Underground storage, on the other hand, is gas that is set aside during the summer months to augment flowing gas provided during the winter heating months. This gas might be drawn down over periods of weeks or months. The following discussion focuses on underground storage, since it is quantitatively much more significant.

To what extent might underground gas

[3] See Solow, et. al., "Value of Improved ENSO Prediction to U.S. Agriculture," *Climate Change*, 39:47-60, 1998.

storage be managed differently if, for example, an upcoming winter is predicted to be warmer due to an El Niño ENSO state? The decision about how much gas to place into storage is driven by the short-run (or variable) costs of storing the gas, on the one hand, and the costs of a gas shortfall, on the other hand. The short-run costs of storage include costs of initial gas injection and holding costs comprised of any physical maintenance costs, possible gas losses during handling and storage, the cost of capital tied up in stored gas, and expected capital gains or losses on gas held in storage. A gas shortfall occurs when firm (i.e. non-interruptible) gas customers do not receive as much gas as they want. This can be very expensive, both directly and in terms of the public relations ramifications for the gas utility. The primary direct cost of a shortfall is the discomfort and inconvenience inflicted on gas users forced to do without gas for a period of time when it is very cold outside. The second direct cost of a shortfall includes having to physically shut off all gas consumers' appliances prior to repressurizing the gas system. This can take a work crew several days for even a relatively small city. Even if a direct gas shortfall is avoided, there are some costs associated with asking interruptible customers to stop using gas. These are the costs to the interruptible customers of switching to a more expensive alternative fuel supply.

It seems likely that the cost of storing gas is relatively small, especially since the price of gas is likely to be lower in the summer and higher in the winter, thereby creating a capital gain on stored gas actually sold before the winter ends. On the other hand, the costs of having insufficient gas available in the winter appear to be very large. The common sense expectation, therefore, is that it is optimal to fill up gas storage facilities more or less completely each summer, regardless of what the forecast for the following winter may be. In other words, the gas storage decision may not be sensitive to a weather forecast.

The story may be different for the decision about drawing down stored gas after the winter peak demand period. At this point, the potential capital gain from storing gas in the summer for sale in the winter will be disappearing. As a result, delaying the sale of gas in storage becomes very expensive at this time. Also, the peak demand period is increasingly likely to have passed, so the expected costs of a shortage of gas diminish steadily as spring approaches. Under these conditions, it makes increasing sense to use any gas remaining in storage, and the timing of such use is a decision that is likely to be influenced by the weather forecast for the remainder of the winter. Thus, it is with respect to this decision that there is likely to be an economic value of improved weather forecasts in the natural gas delivery system.

Fuel oil is another energy source used for space heating. Fuel oil is made from crude petroleum in refineries that also produce gasoline and other products derived from petroleum. Crude petroleum itself is delivered to refineries by pipeline and/or ships. Refined products may be delivered from the refinery by pipeline, railroad, trucks, ships or a combination.

Like pipelines, refineries are expensive long-lived pieces of capital that are not built, retired, or put to another use in anticipation of a colder or warmer winter. However, different crude oils may be run through refineries to change the output mix of the refinery, and refinery processes may also be adjusted to change the output mix. In this way, the output of fuel oil may be increased in the winter, and the output of gasoline increased in the summer.

In contrast to the situation with natural gas, the fuel oil delivery system is somewhat flexible, since much of the delivery system can be reconfigured quickly in response to changes in local demands for fuel oil. That is, trucks, railroad cars, and ships can be redeployed from other geographic regions to meet a sudden increase in demand in one particular region. Consequently, a local peak in demand can often be met by redirecting fuel oil deliveries from other areas not simultaneously experiencing a peak in demand. Thus, in a fuel oil delivery system, the peak demand that must be considered is one averaged over a large geographic area, and this is likely to be a smaller peak relative to average demand.

Still, changing the refinery output mix and redirecting fuel oil deliveries are not by themselves sufficient to meet winter peak demands for fuel oil. Thus, as with natural gas, fuel oil is also stored to meet winter peak demands. Fuel oil storage may exist at many locations in the refining and distribution chain, including at ports (in the case of imported fuel oil), at the refinery, at distribution facilities located near markets, and even at the point of use. In fact, storage at the point of use may be quite significant, since a typical residence using fuel oil might store enough for a month's usage during the winter. Since many fuel oil customers have contracts for automatic oil deliveries, it would be possible for retail fuel distributors to make some use of storage at customer locations, by appropriately adjusting their delivery schedules. Overall, however, storage appears to be a relatively less important component of the fuel oil delivery system than it is for the natural gas system.[4]

Unlike the situation in natural gas, an actual winter shortfall of fuel oil seems to be a very unlikely occurrence. This is presumably because the oil delivery system has sufficient flexibility to increase production and/or redirect supplies so that actual shortages do not occur. Thus the decision about how much fuel oil to store is driven by the variable costs of storing oil, on the one hand, and the expected value (i.e. price) of oil during the winter season, on the other hand. The costs of storing fuel oil include injection and holding costs such as physical maintenance costs, possible (presumably small) losses during handling and storage, and the cost of capital tied up in stored oil. These storage costs must be weighed against the expected capital gain from holding oil, which is the difference between the price of the oil at the time of storage and the expected price at the time of withdrawal and sale.

In general, one should expect that the capital gain from storing fuel oil would exceed the variable costs of storing oil. In fact, in long run equilibrium, the capital gain should exceed variable costs of storage by enough to pay the annualized capital cost of installing storage capacity. For this reason, it will almost always make sense to fill storage capacity prior to the peak demand season. In this regard, the situation with fuel oil is the same as that with natural gas.

Regarding the drawdown of stored fuel oil during and after the peak in winter demand, the situation may again be similar to that for natural gas. That is, when there is a forecast of a warmer winter, the drawdown of fuel oil stocks would begin sooner and proceed faster than otherwise. This means that we should look to the decisions about optimal fuel oil storage drawdown to find an economic value of an improved weather forecast based on prediction of the ENSO state.

D. Hydroelectric Management

Electricity generated from water power is a relatively small component of total U.S. electric production. However, hydroelectric power is very cheap to produce, once the capital stock is in place. Thus, whenever possible, electric generating authorities would prefer to use the hydroelectric power instead of some more expensive oil, gas, or coal fired generation facility. Nature, however, provides the water to produce hydroelectric power, and it does so in somewhat unpredictable amounts. Moreover, there are often other competing uses for water, such as agricultural irrigation, recreation, and ecosystem maintenance. For these reasons, the use of water for hydroelectric power generation is usually carefully controlled so that other water users are not compromised.

In view of the above, it is clear that improved forecasts of precipitation would affect decisions about the use of hydroelectric generation capacity. For example, if an upcoming wet season is reliably predicted to be wetter than normal, somewhat lower water reserves might be carried into the wet season, and somewhat higher water use might be appropriate in the early weeks of a wet season. The converse would be true if an upcoming wet season is reliably predicted to be dryer than normal. Thus, it seems apparent that there would be an economic value of improved information in the operation of hydroelectric generating facilities.

E. Construction

[4] Storage is about 10 percent of annual consumption for gas versus about 1 percent for petroleum products. Storage in each case is defined as the monthly maximum amount in storage minus the monthly minimum amount over the last two or three years. This calculation automatically excludes the large amount of oil in the Strategic Petroleum Reserve.

In the case of construction, it was noted above that this economic activity may be more efficiently carried out when weather conditions are favorable. It would also seem that an improved weather forecast might affect decisions made in construction activities. For example, it may be more efficient to carry a given project through to completion, rather than starting and later suspending work due to unfavorable weather. In some cases, the inefficiency of stopping and restarting may be such that the project is simply put off until some later time when the chance of having to stop is very small. In such cases, a weather forecast that clarified the prospects for being able to carry a project through to completion might affect when the project is started. Thus there could be an economic value of better weather information in the construction industry.

F. Outdoor Recreation

Finally, we come to outdoor recreation. As an example, consider skiing. From the point of view of the ski resort operator, there is little reason to think that an improved weather forecast for the upcoming ski season would affect his or her decisions about how to manage the resort. The amount of natural snow received would presumably affect costs of maintaining the ski slopes and costs of keeping parking lots cleared of snow, but it seems unlikely that it would affect the number of snow making machines or snow clearing crews available for a given season.

On the other hand, the vacation choices of skiers might change significantly in response to better information about weather conditions in ski areas. Skiers might make different choices about where to go for a skiing vacation, or even whether to take a skiing vacation, as opposed to something else, such as snorkeling in the Caribbean or touring the restaurants of France. From the point of view of operators of outdoor recreation facilities, revenues and profits would be more variable over time, but would presumably be about the same or slightly higher on average.[5] From the point of view of participants in outdoor recreation activities, the overall utility or perceived benefits of participation would be higher. Thus there is reason to think that there would be an economic value of improved weather forecasts in outdoor recreation activities.

[5] To the extent that better weather information created greater demand for outdoor recreation (because a spoiled vacation is easier to avoid), revenues and profits would be higher.

The Economic Consequences of El Niño and La Niña Events for Agriculture[1]

Richard M. Adams, Chi Chang Chen, Bruce A. McCarl, Rodney Weiher

Abstract

Climate is the primary determinant of agricultural productivity. In many parts of the world, including the United States, one can trace much of the year-to-year variations in climate to the El Niño-Southern Oscillation phenomenon. In 1997-98 the world experienced a severe El Niño event and this is being followed by a strong 1998-99 La Niña. This research develops estimates of the economic consequences of such events on U.S. agriculture. Both phases result in economic damages—a $1.5 to $1.7 billion loss for El Niño and a $2.2 to $6.5 billion loss for La Niña. The major conclusion is that ENSO events impose costs on agriculture and consumers.

Introduction and Background

Climate is the primary determinant of agricultural productivity. An important aspect of climate in terms of human well being involves the effects on agriculture of seasonal and interannual variation in temperature and precipitation. The effects of drought and flooding provide the clearest evidence of the vulnerability of agriculture and food supplies to seasonal variations in temperature and precipitation. However, less dramatic climate variations also are reflected in agricultural production, prices, and profits. In many parts of the world, including the United States, one can trace much of the year-to-year variations in climate to the El Niño-Southern Oscillation phenomenon.

The El Niño-Southern Oscillation (ENSO) label refers to a quasi-periodic redistribution of heat and momentum in the tropical Pacific Ocean. In broad terms, one can characterize ENSO as a varying shift between a normal phase and two extreme phases: El Niño and La Niña (sometimes called El Viejo). In recent years, the ability to forecast ENSO events, in particular, the occurrence of El Niño events, has improved (Barnett et al., 1988; Cane et al., 1986, Bengtsson et al., 1993). These forecasts have potential economic value because they can stimulate actions that mitigate against adverse consequences or take advantage of potential gains from an ENSO phase.

The 1997-98 El Niño is regarded as one of the most severe in the past decade and perhaps equal to the strong El Niño of 1982-83. The physical effects of this El Niño were felt through much of the Southwestern and Eastern United States, with heavy rains and flooding throughout the winter and spring in California and Arizona and a mild, but wet winter and spring in the northeast. Preliminary evidence from weekly crop prices suggests that disruptions of certain high valued spring crops in California imposed substantial costs. For example, reductions in California strawberry marketings in the spring of 1998, due primarily to flooding, resulted in losses to consumers of over $15 million compared to 1997 prices and nearly $100 million compared to the average price for the previous ten years, based on estimates of seasonal demand relationships for strawberries.

By the summer of 1998, there was evidence

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that the waning 1997-98 El Niño was moving rapidly into a La Niña phase, with a dramatic cooling of ocean surface temperatures in the southern Pacific Ocean. Like El Niño events, La Niña's also have specific regional "footprints" but with a general reversal of the weather patterns observed during El Niño's (e.g., colder but drier winters in the western U.S.). These La Niña events also have effects on agriculture and other sectors.

The damages associated with the recent El Niño demonstrate that ENSO events have potential economic consequences for agriculture and other sectors of the economy; recent studies show that the use of forecasts of these events has economic value (Adams et al., 1995; Costello et al., 1998; Solow et al., 1998). The agricultural values for such forecasts have been estimated to be in excess of $300 million per year (1992 dollars). However, the actual damages from a given ENSO event will be greater than the value of the forecasts since in general not all damages can be avoided and forecasts are not perfect. Estimates of actual or produced damages from ENSO events can be useful to policy makers in determining first whether such events are important relative to other natural processes and second, whether the potential damages from a future event, such as the developing La Niña, merit vulnerability reducing actions.

Objectives

The work underlying this report was designed to develop estimates of the economic consequences of the recent (1997-98) El Niño event and to assess possible effects of the forecast 1998-1999 major La Niña event on U.S. agriculture. Both estimates are prospective, in that the final effects of the 1997-98 El Niño on agriculture will not be understood until final data of the 1998 harvests and yields becomes available. Similarly, the full effects of a prospective La Niña on agriculture will not be realized for at least twelve months. However, the historical climatological record, which includes years reflecting all three ENSO phases, does provide some indications as to how weather and associated crop yield data has varied during such ENSO phases. Thus, the analyses reported here can be viewed as assessments of the effects of moderate to strong ENSO events.

Historical weather and yield occurrences, measured as departures from normal (long term average) yields, are used here as a measure of the effects of the most recent El Niño and the pending La Niña events. In addition, modeled yield changes for such ENSO events, taken from a recent study (Solow et al., 1998) are also used. The Solow et al study involved modeled (simulated) crop yield changes and may well provide a clearer picture than historical yield deviations of the effects of weather, given that the historical data on crop yields may contain effects from other factors, such as crop diseases, changes in farm programs or other non-weather phenomenon.

The yield changes for El Niño, Normal and La Niña events arising from both the historical record and model simulations are used as input into an economic model of the U.S. agricultural sector. This model is used to estimate the effects of these ENSO events on prices, crop supplies and the welfare of consumers and producers. Procedures underlying this simulation of ENSO events, including data and the economic model, are discussed in more detail in the next section. The following section presents results of these simulated ENSO events. Implications and conclusions of these estimates are presented in the final sections of this report.

Data and Models

This assessment of the damages from ENSO events involves a two stage process. In the first stage, the consequences of the changes in weather patterns due to ENSO phases on crop yields are measured using estimates from both crop biophysical simulation models and historical yield data. The second stage incorporates these yield differences into an economic model in order to assess the aggregate economic damages of ENSO events.

Crop Yield Changes

The first set of yield estimates are taken from Solow et al. and are based on output from a crop simulation model. Specifically, estimates of the yield implications of weather changes from each

ENSO phase for eight field crops (corn, wheat, soybeans, cotton, barley, sorghum, oats and hay) were developed using a biophysical simulation model called Erosion Productivity Impact Calculator or EPIC (Williams et al., 1984; Williams et al., 1989). EPIC has been used in numerous studies for a variety of purposes and has gained popularity across disciplines in agriculture. EPIC has been shown to provide reasonable simulations of crop yields in previous ENSO studies (Bryant et al., 1992). Details of the EPIC application to ENSO events can be found in Adams et al. and Solow et al. Specific crop yield data for ENSO phases are reported in Solow et al. and Legler, Bryant and O'Brien.

The second approach to estimating yield consequences of ENSO phases is based on twenty-five years (1972-1996) of crop yield data for all crops included in the economic model (the eight listed above plus citrus and some minor crops). The yield data are taken from USDA publications, including *Agricultural Statistics* (various years). These yield data are first detrended (to remove the effects of technological change and acreage shifts on yields) and then yield estimates are projected for each year. In turn, the deviations between the projected and actual yields are recorded as a percentage change from the projected yields. Finally these deviations were applied to the 1997 yield projection to obtain a joint probability distribution across 63 US regions based on the 25 historic weather events. This distribution reflects, among other factors or influences, the variation due to weather, including the ENSO phase.

Economic Modeling Procedures

The yield distributions, from both the EPIC estimates and historical data, are used in defining the economic model used in this assessment framework. Specifically, the changes in yields are used in an economic model of the U.S. agricultural sector, identified as the Agricultural Sector Model or ASM (see Chang and McCarl, 1992, for details) within a stochastic framework (Lambert et al). This economic model provides the mechanism for translating the physical (yield) effects of ENSO changes into economic effects, including net changes in economic welfare, as well as changes in supply and prices for major agricultural commodities. Variants of this model are used in Adams et al., Solow et al., and a number of other assessments of the consequences of environmental change.

The economic model is a price endogenous model formulated as a mathematical programming problem (McCarl and Spreen). The model represents production and consumption of 30 primary agricultural products including both crop and livestock products. Processing of agricultural products into 12 secondary commodities also is included. Prices for these commodities are determined endogenously for both national and international (export) markets. The model maximizes the sum of the area under the demand curves but above the price (consumer surplus) plus the area above the supply curves but below the price (producer surplus) for these commodities. One can interpret changes in this area as a measure of the economic welfare equivalent of the annual net income lost or gained by agricultural producers and consumers as a consequence of crop yield or other changes, expressed in 1997 dollars. Both domestic and foreign consumption (exports) are included.

The model takes regional level responses and aggregates these to national level responses. Specifically, producer-level behavior is captured in a series of technical coefficients that portray the physical and economic environment of agricultural producers in each of the 63 homogeneous production regions in the model, encompassing the 48 contiguous states. The analysis also considers irrigated and non-irrigated crop production and water supply relationships. Availability of land, labor, and irrigation water is determined by supply curves for each input. Farm-level supply responses generated from the 63 individual regions are linked to national demand through the objective function of the sector model, which features demand relationships for various market outlets for the included commodities.

Certain assumptions and procedures are required to use ASM to estimate economic damages from actual or prospective ENSO events:

- The base economic model is keyed to 1990 economic, agriculture, and environmental conditions.

- The EPIC yield forecasts and selected historical yield deviations are assumed to reflect accurately the consequences of the 1997-98 El Niño and the 1998-99 La Niña.

As noted above, the yield changes measured by historical records reflect all sources of yield variation, not just the ENSO-specific influences. The EPIC forecasts, to the extent that they are tailored to specific weather conditions associated with ENSO phases, are expected to more accurately reflect such events. Taken together, however, both sets of yield changes provide evidence of the consequences of these ENSO events on the agricultural economy of the U.S.

Results

The two phase assessment procedure defined above can be viewed as a set of "experiments" to measure the potential consequences on U.S. agriculture of as yet unrealized events (in this case, the final effects of a major El Niño in 1997-98 and a possible La Niña event in 1998-99). These experiments provide an indication of how two strong ENSO events may affect the aggregate (national level) welfare of the agricultural sector.

The results from these experiments reflect a range of weather and yield conditions. For example, the yield and subsequent economic consequences elicited here reflect historical frequencies of each phase. To capture these, the economic model is run (solved) under a series of uncertain events (three in the EPIC analysis and 25 in the "historical" yield case) based on the long run probability of these events occurring. These sets of model runs are used to determine average or "normal" conditions from which the El Niño and La Niña economic effects will then be inferred. In the EPIC-based analysis, the El Niño and La Niña results do not correspond to a particular year; rather, they represent the weather and resultant yield changes for years identified by each phase. In the "historical yields" case, two time periods from the twenty-five year record are used to portray possible effects of each phase; 1982-83 for the El Niño and 1988-89 for La Niña. Both time periods reflect years identified by climatologists as strong phases of each event. The economic consequences under this latter approach are measured as departures from the "normal" phase (neither El Niño nor La Niña).

The results of these experiments are provided in Tables 1 and 2. In Table 1, results from the EPIC-based simulations of each ENSO phase or event are reported. As is evident from the table, both phases result in economic damages relative to the Normal phase or case (of -$1.5 for El Niño and -$6.5 billion for La Niña, respectively). For the historical case, both ENSO phases again show losses (economic damages) although of a smaller magnitude. Here, the economic damages of El Niño and La Niña are $1.7 and $2.2 billion, respectively. While the results of the EPIC-based analysis are greater than those from historical data, the important finding is that these events translate into economic damages for agriculture under both sets of assumptions regarding yield changes. It is also worth noting that the optimization nature of the economic model used here results in estimates that reflect some internal actions (such as changes in crop mixes) to offset or mitigate against the negative consequences of the changes in yields. Thus, the estimates are lower bounds on damages.

The overall implication of these findings regarding ENSO phases is not surprising; extreme events, whether driven by El Niño or La Niña weather patterns, have adverse consequences for agriculture (at the national level). To the extent that some of these agriculture effects can be mitigated or offset by planning, there is value in forecasting such ENSO phenomenon. Previous studies have confirmed the value of such forecasts.

Conclusions

ENSO events have varying effects on temperature and precipitation across agricultural regions of the U.S. For some regions, these changes in seasonal weather may be beneficial. However, for other regions the effects can be dramatic and severe, such as the floods in the southwest during the spring of 1998. These sets of effects translate into economic effects if crop yields are reduced (or increased) from expected or "normal" levels.

The results of the experiments performed here indicate that overall, the effects of both extreme ENSO phases are negative for U.S. agriculture. Measured as departure from normal (non El Niño or La Niña) yields, the consequences vary from approximately $1.5 billion to $6.5 billion in losses. The range reflects assumptions concerning how yields are estimated and whether it is an El Niño or La Niña event. The estimates reported here must be viewed in the context in which they are generated. As estimates from a modeling exercise, the numbers reflect a series of embedded assumptions and are conditional on the quality of data used in the economic modeling and in the generation of the yields used to capture the various ENSO phases. The major conclusion is that extreme weather events, such as the ENSO events, do impose costs on agriculture and consumers. The magnitude of these cost estimates support concerns over the likely increase in extreme weather phenomenon under a warming global atmosphere.

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Table 1. Estimates of Strong El Niño and La Niña Events, Using Simulated Crop Yield Changes.

ENSO Event	Economic Consequences[2] (millions of 1990 dollars)
El Niño[1]	-2,543
La Niña[1]	-6,455

[1] The weather patterns used as inputs to the EPIC model reflect or simulate a "strong" ENSO event.

[2] Economic consequences (damages) reported here are measured against an average or "base case" derived by using historical frequencies of all three ENSO phases.

Table 2. Estimates of Strong El Niño and La Niña, Using Historical Crop Yield Changes.

ENSO Event	Economic Consequences[2] (millions of 1990 dollars)
El Niño[1]	-1,739
La Niña[1]	-2,247

[1] The historical analogue used to represent the 1997-98 El Niño is the 1982-83 El Niño.

[2] The historical analogue used to represent the 1997-98 La Niña is the 1988-89 La Niña.

Effects of 1997-1998 El Niño on Natural Gas and Distillate Fuel Oil Costs

Thomas J. Teisberg

Summary

The El Niño event of 1997-1998 caused above normal temperatures which significantly reduced space heating requirements for the US, especially in January and February 1998. The purpose of this note is to present some estimates of the fuel cost savings that resulted from this reduction in space heating requirements. Estimates are provided for natural gas used in the residential and commercial sectors, and for total distillate fuel oil use.

The analytical approach employed for each type of fuel and/or fuel use is to statistically estimate an historical relationship between fuel use and heating degree days (HDD). Then this relationship is used to estimate the fuel use change caused by the monthly departures from normal HDDs during the winter of 1997-1998. Finally, the monthly changes in fuel use are valued using recent fuel prices. The result is an estimated cost savings due to the warmer winter of 1997-1998. The total cost savings for the three fuel/uses and for October 1997 through April 1998 is more than $2 billion. Table 1 on page 20 summarizes the results of this analysis. These results are also displayed graphically in Figures 1 through 3, also on page 23.

[1] The 1984 initial year is the first for which gas consumption data were conveniently available electronically. The 1992 final year is the last for which historical HDD data were conveniently available. There is no reason to think that extending the data series forward or backward in time would significantly change the estimated relationships between consumption and HDDs.

Analytical Notes

A. Relationship between HDD and consumption

For residential gas, commercial gas, and total distillate fuel oil use, data were collected on consumption and heating degree days, by month, for the period 1984 through 1992. These data were used to estimate relationships between fuel consumption and heating degree days. Figures 4, 5, and 6 show the data points and fitted relationships for the three fuel/use categories. The slopes of the fitted trendlines represent the change in fuel use per heating degree day; these slopes are used to estimate the changes in fuel use attributable to departures from normal of heating degree days. Table 2 on page 23 indicates the slopes for the three fuel/use categories.

Estimated Changes in Fuel Consumption

Normal and actual heating degree day statistics for the U.S. were obtained for the months from October 1997 through April 1998. These are shown in Table 3 below, together with the departures from normal.

The departures from normal of heating degree days shown in Table 3 are multiplied by the coefficients in Table 2, to obtain estimated change in fuel use for each month and each fuel use. These calculations are shown in Table 4 on page 24.

Fuel Cost Savings

Fuel cost savings are obtained by multiplying the monthly estimated fuel use changes by fuel prices for the corresponding months. Using price data from a single year excludes from the estimated cost savings any effects of prices changes between years. Such price changes might or might not be properly attributed to El Niño. Table 5 on page 25 shows the fuel prices used in the calculations.

Finally, Table 6 on page 26 details the calculations of estimated cost savings by month and fuel/use.

Appendix: Data Sources

1. Residential and commercial natural gas consumption for 1984-1992 were extracted from GASCON.EXE available at ftp.eia.doe.gov/pub/natural.gas/monthly.

2. Historical heating degree days for 1984-1992 are from Table 1.8 of EIA Annual Energy Review 1996.

3. Distillate fuel oil consumption for 1984-1992 are from private communication from Jonathan Cogan (Jonathan.Cogan@eia.doe.gov). I assume these are also available in print form.

4. Heating degree days for winter 1997-1998 are from relevant issues of Monthly Energy Review, Table 1.11.

5. Residential natural gas prices for winter 1997-1998 are from Natural Gas Monthly, Table 21, August 1998.

6. Commercial natural gas prices for winter 1997-1998 are from Natural Gas Monthly, Table 22, August 1998.

Table 1
Fuel Cost Savings in Winter 1997-1998
(Million $)

	Residential Gas	Commercial Gas	Distillate Fuel Oil
October 1997	-126	-42	-26
November 1997	-300	-114	-70
December 1997	127	49	31
January 1998	899	346	218
February 1998	700	269	169
March 1998	27	10	7
April 1998	15	5	3
October - March	1341	524	332

Table 2
Change in Fuel Use
per Unit Change in HDD

Fuel/Use Category	Change in Use per Unit Change in HDD
Residential Gas	.718 BCF/HDD
Commercial Gas	.320 BCF/HDD
Distillate Fuel Oil	1214 thousand gals/HDD

Table 3
Heating Degree Days for Winter 1997-1998

	Normal	Actual	Departure
October 1997	271	294	23
November 1997	528	589	61
December 1997	836	809	-27
January 1998	948	754	-194
February 1998	768	616	-152
March 1998	611	605	-6
April 1998	339	336	-3

Table 4
Estimated Changes in Fuel Use

Part 1 - Residential Gas

	Departure	Residential Gas Coefficient	Est. Fuel Use Change (BCF)
October 1997	23	.718	16.5
November 1997	61	.718	43.8
December 1997	-27	.718	-19.4
January 1998	-194	.718	-139.4
February 1998	-152	.718	-109.2
March 1998	-6	.718	-4.3
April 1998	-3	.718	-2.2

Part 2 - Commercial Gas

	Departure	Commercial Gas Coefficient	Est. Fuel Use Change (BCF)
October 1997	23	.320	7.4
November 1997	61	.320	19.5
December 1997	-27	.320	-8.6
January 1998	-194	.320	-62.1
February 1998	-152	.320	-48.6
March 1998	-6	320	-1.9
April 1998	-3	.320	-1.0

Part 3 - Distillate Fuel Oil

	Departure	Distillate Fuel Oil Coefficient	Est. Fuel Use Change (thou. gal.)
October 1997	23	1214	27924
November 1997	61	1214	74059
December 1997	-27	1214	-32780
January 1998	-194	1214	-235530
February 1998	-152	1214	-184539
March 1998	-6	1214	-7284
April 1998	-3	1214	-3642

Table 5
Fuel Prices

	Residential Gas ($/mcf)	Commercial Gas ($/mcf)	Residential Distillate ($/gal)
October 1997	7.65	5.73	.921
November 1997	6.85	5.84	.941
December 1997	6.55	5.72	.938
January 1998	6.45	5.57	.925
February 1998	6.41	5.54	.915
March 1998	6.26	5.36	.896
April 1998	6.74	5.54	.876

Table 6
Estimated Cost Savings

Part 1 - Residential Gas

	Est. Fuel Use Change (BCF)	Residential Gas Price ($/mcf)	Est. Cost Savings (Million $)
October 1997	16.5	7.65	-126
November 1997	43.8	6.85	-300
December 1997	-19.4	6.55	127
January 1998	-139.4	6.45	899
February 1998	-109.2	6.41	700
March 1998	-4.3	6.26	27
April 1998	-2.2	6.74	15

Part 2 - Commercial Gas

	Est. Fuel Use Change (BCF)	Commercial Gas Price ($/mcf)	Est. Cost Savings (Million $)
October 1997	7.4	5.73	-42
November 1997	19.5	5.84	-114
December 1997	-8.6	5.72	49
January 1998	-62.1	5.57	346
February 1998	-48.6	5.54	269
March 1998	-1.9	5.36	10
April 1998	-1.0	5.54	5

Part 3 - Distillate Fuel Oil

	Est. Fuel Use Change (thou. gal.)	Residential Distillate ($/gal)	Est. Cost Savings (Million $)
October 1997	27924	.921	-26
November 1997	74059	.941	-70
December 1997	-32780	.938	31
January 1998	-235530	.925	218
February 1998	-184539	.915	169
March 1998	-7284	.896	7
April 1998	-3642	.876	3

Case Study of 1997-98 El Niño for Minnegasco

Richard A. Nichols

Reliant Energy Minnegasco is the largest natural gas distribution company in Minnesota serving more than 604,000 residential customers and 57,000 business customers, including the Minneapolis metro area. Space heating load represents most of the energy demand for the entire year, but more specifically in the mid-October to mid-April season. Daily total system load varies from a peak of 1,082,371 Mmbtu to a minimum of 109,084 Mmbtu. Normal heating degree days (hdd) using a 65 degree base of average daily temperature and a twenty year rolling average assumption is 7,761 hdd.

The design day assumption is for 90 hdd or 25 degrees average daily temperature. Minnegasco, in addition to delivered pipeline capacity from the south, north, and west, operates and receives gas delivery from underground storage, propane, and LNG (liquefied natural gas) peak shaving facilities and curtails interruptible, dual-fuel customers with as short as one hour notice.

Accurate weather forecasts are crucial to system operation and considerable economic efficiencies are realized on price, maintenance scheduling, and storage reserves injection when improved seasonal weather forecasts are used. Although daily dispatching, system operation, and scheduling occurs every day up to five days ahead, seasonal weather forecasts play a large role in the monthly planning and heating season preparation to ensure that system operational reliability and capability is realized to meet customer peak demand requirements. The dispatch center subscribes to two major weather forecasting services. One is from a local provider and the other from a large national service with a long list of utility clients. NOAA and other web weather forecast services are monitored as well. The NOAA El Niño web page and links to other specialty research organizations opened up new information reference sources for longer term weather outlooks related to El Niño and La Niña events. Many of the internet-available weather forecasts are restatements or slightly altered NOAA generated weather forecasts. This provides confirmation and continuity across forecasters, but not much in value-added content to the prediction output. More accurate long- and short-range weather forecasts would provide considerable economic benefit.

The El Niño forecast and event of the 1997-98 heating season resulted in only 5,624 hdd which is 9.9 percent warmer than the normal assumption. The extreme warmth of the 1997-98 winter season either set or came close to many long-run historical records. The most recent previous winter season experiencing this level of warm or above normal temperatures was in 1986-87, also an El Niño event. As the 1997-98 winter season progressed by month, the mild temperatures appeared to gain in frequency, persistence, and dominance. For us, the weather news just continued to get worse, even through the spring. Some of our actions included the following:

- High gas prices and a warm winter forecast resulted in some storage capacity and peak shaving facilities not being as full as under normal circumstances.

- An insurance hedge policy was proposed and negotiated that would have nearly maximized the payout ceiling. Other companies did execute such agreements and many reduced their budget shortfall by one-half. Future utilization of this type of financial tool would again be considered.
- Curtailment activity was substantially reduced to less than ten percent of the projected level under normal weather.
- Operational efficiencies were exploited to the greatest extent possible to help reduce costs and as the warm weather persisted, gas prices softened and fell providing additional customer savings. Our performance-based ratemaking (PBR) pilot program resulted in a large and favorable reward incentive to the company's stockholders and customers. The PBR program compares our financial performance parameters to our own benchmark and to other area utilities. The PBR reward demonstrated the magnitude and success of our cost-cutting efforts driven in part from the El Niño forecast.
- Due to the lack of snow, warm temperatures, and the early spring, construction and maintenance activities started earlier and better planning and scheduling reduced many cost factors such as overtime pay. In spite of another year of rapid customer growth, new added services have proceeded with minimal delays.

Long-term weather forecasts for El Niño type events need to be identified with the detail of statistical confidence. Business risks could be evaluated in a more probabilistic approach allowing for higher levels of certainty. A future El Niño event would likely result in an insurance hedge if confidence in forecast accuracy is high. Storage and peaking facilities fill level and rate would be driven more by price and less by attempting to reach maximum levels as well as estimation of the required operational levels needed for warmer than normal weather events.

Due to the wide variety of weather forecaster's opinions, we believe access to historical sea surface temperature data and maps would be useful analysis and decision support. For example, NOAA pointed to the 1982-83 El Niño as a similar event for the 1997-98 El Niño forecast. Others identified 1957-58 and 1991-92 as their forecast for 1997-98. The 1976-77 El Niño event was actually substantially colder than normal and raised the question of 'what if?'. Having web access to past sea surface temperature maps would allow independent determination and assessment of the best forecast scenario by those taking the risk.

The Value of Improved ENSO Prediction to U.S. Agriculture[1]

Andrew R. Solow, Richard F. Adams, Kelly J. Bryant, David M. Legler, James J. O'Brien, Bruce A. McCarl, William Nayda and Rodney Weiher

Abstract

The economic value of long-range weather prediction is measured by the increase in social welfare arising from the use of the prediction in economic decisionmaking. This paper describes a study of the economic value of ENSO prediction to U.S. agriculture. The interdisciplinary study involved the analysis of data and models from meteorology, plant science, and economics under a framework based on Bayesian decision analysis. The estimated annual value of perfect ENSO prediction to U.S. agriculture is $323 million.

Introduction

Skill in interannual climate prediction has improved over the past decade. This improvement is due in large part to the ability to predict, up to a year in advance, oceanographic conditions in the equatorial Pacific Ocean relating to the phenomenon known as El Niño-Southern Oscillation (ENSO). A recent comprehensive review of ENSO prediction is given in Latif et al. (1994). Public investment in data acquisition, modelling studies, and other scientific activities should lead to further improvements in ENSO prediction and, as a result, to further improvements in climate prediction. For this reason, there is an interest in assessing the return to investment in this area.

In a previous study, Adams et al. (1995) estimated the value of improved ENSO prediction to agriculture in the southeast U.S. This paper describes an extension of the earlier study to all U.S. agriculture. Beyond its enlarged scope, the present study differs from the previous one in two respects. First, the report of the previous study was aimed primarily at economists. In contrast, the present paper stresses the interdisciplinary aspects of the study. Second, the present study improves on the previous one in certain technical areas, including a more comprehensive treatment of climate statistics and crops and improved modeling of decisionmaking under uncertainty.

The basic scenario considered here is the following. The ENSO year runs from October to September. Each ENSO year can be classified according to ENSO phase. There are three ENSO phases: warm event (or El Niño), cold event (or El Viejo), and nonevent. Climate in the U.S. is affected by ENSO phase, although not all regions are affected and, those that are affected, are not necessarily affected in the same way. The regional climatic differences between different ENSO phases affect the yields of different crops. Thus, advanced knowledge of ENSO phase provides advanced knowledge of climatic conditions, which in turn provides advanced knowledge of agricultural yields. Since different crops respond differently to climatic conditions, advanced knowledge of yields provides information about the profitability of different cropping patterns. Individual farmers use this information about profitability in selecting their cropping patterns. The consequences of these individual decisions for the agricultural sector and ultimately for consumers are captured through the market for agricultural products.

[1] *Climatic Change*, 39:47-60, 1998.

In broad terms, the economic effect of improved ENSO prediction is the same as that of a technological improvement that increases the supply of agricultural products. The value to society of this shift in supply is the increase in the sum of consumer and producer welfare. The sum of these is referred to as economic surplus. Briefly, changes in consumer welfare reflect gains (or losses) due to lower (or higher) prices, while changes in producer welfare reflect changes in so-called quasi-rents, which in most cases are comparable to profits. The economic value of ENSO prediction is defined as the expected chance in economic surplus arising from changes in cropping pattern due to the prediction.

To use this scenario as a basis for estimating the value of improved ENSO prediction, it is necessary to model:

- the climatic differences between different ENSO phases;
- the effects of these climatic differences on yields;
- the way in which information about yields affects planting decisions; and
- the way in which the behavior of individual farmers affects the market of agricultural products. These steps are described in the following sections.

Climatic Differences Between ENSO Phases

The first step in estimating the differences in monthly climate between the three ENSO phases was to classify each ENSO year in the 40-year study period 1947-1986 by ENSO phase. The classification rule was based on a 5-month moving average of the average sea surface temperature anomaly within the tropical Pacific region 4° S - 4° N, 150° W - 90° W constructed by the Japan Meteorological Agency. If the index exceeded 0.5°C

Table I

ENSO phase categorization, 1947-1986

Normal	El Niño	El Viejo
1950	1951	1947
1952	1957	1948
1953	1963	1949
1958	1965	1954
1959	1969	1955
1960	1972	1956
1961	1976	1964
1962	1982	1967
1966	1986	1970
1968		1971
1974		1973
1977		1975
1978		
1979		
1980		
1981		
1983		
1984		
1985		

Table II

Stations used to define agricultural regions

Place	State	Place	State	Place	State
Muscle Shoals	AL	Lafayette	LA	Corpus Christi	TX
Union Springs	AL	Big Rap. Wat.	MI	El Paso	TX
Mesa Exp. Farm	AZ	Greenville	MS	Liberty	TX
Pocahontas	AR	Moorhead	MS	Marshall	TX
Davis	CA	Chinook	MT	Mexia	TX
Napa St. Hosp.	CA	Santa Rosa	NM	Muleshoe	TX
Redlands	CA	Kinston	NC	Snake Creek	UT
Fort Morgan	CO	Mt. Airy	NC	Columbia	VA
Bridgeville	DE	Mott	ND	Pullman	WA
Apalachicola	FL	Towner	ND	Buckhannon	WV
Ocala	FL	McConnelsville	OH	Spooner	WI
Covington	GA	Wooster	OH	Viroqua	WI
Aberdeen	ID	Geary	OK		
Duquoin	IL	Mangum	OK		
Monmouth	IL	Dufur	OR		
Berne	IN	Wellsboro	PA		
Clarinda	IA	West Chester	PA		
New Hampton	IA	Newberry	SC		
Independence	KS	Cleark	SD		
Bowling Green	KY	Alice	TX		
Owensboro	KY	Ballinger	TX		

for 6 consecutive months including October-December, then the ENSO year was classified as El Niño phase. If the index fell below -0.5°C for 6 consecutive months including October-December, then the year was classified as El Viejo phase. All other years were classified as nonevent phase. The classification, which is similar to others (e.g., Kiladis and Diaz, 1989), is given in Table I.

Using this classification, monthly climate statistics were calculated for each ENSO phase at each of 54 stations. These stations, which are listed in Table II, were selected to provide balanced coverage of agriculturally significant regions. An agricultural region was associated with each of these stations. Both the climate differences between ENSO phases and the corresponding yield effects were assumed to be constant within these regions. Daily climate data for the representative stations were used to calculate monthly mean values of the following climate statistics:

- mean and standard deviation of daily minimum and maximum temperature;
- mean, standard deviation, and coefficient of skewness of daily precipitation;
- the number of wet days; and
- the one-step transition probabilities between wet and dry days.

The selection of these statistics, which are more comprehensive than those used in the previous study, was based on a sensitivity analysis of the yield model described in the following section.

Details of this analysis, including an assessment of the statistical significance of observed climatic differences between ENSO phases, are presented in Sittel (1994a, b). Some selected results are shown in Figure 1. In broad terms, climatic differences between the phases are greatest during winter. In the southeastern U.S., where the ENSO signal appears to be most pronounced, El Niño years tend to be colder than normal in the fall and winter and warmer than normal in the spring and summer. El Viejo years generally exhibit patterns with the opposite sign, although typically not the same magnitude. For precipitation, El Niño years tend to be wetter than normal in the winter and spring and dryer than normal during the summer. Again, El Viejo years generally exhibit patterns of opposite sign, but different magnitude. These results are generally consistent with those found in other studies (e.g., Ropelewski and Halpert, 1986).

Yield Effects

The crops included in this study were barley, corn, cotton, hay, potatoes, rice, sorghum, soybeans, tomatoes, and wheat. This selection was based primarily on economic importance and on planting schedules, which determine the potential for incorporating long-range weather prediction into planting decisions. These crops account for over 90% of acreage and 80% of farm gate value in the U.S. For each crop, the effect of yield of climatic differences between ENSO phases were estimated for each region using a plant biophysical simulation model called the Erosion Productivity Impact Calculator (EPIC). This model, which is described in Williams et al. (1989) and Bryant et al. (1992), was originally developed to determine the relationship between soil erosion and productivity. However, because it uses climatic information in calculating yield, it is well-

Table III

Simulated crop yields under difference ENSO phases for selected stations. Values are bushels per acre for corn, soybean, wheat; pounds of lint per acre for cotton; and hundred pounds per acre for sorghum

	Normal	El Niño	El Viejo
Mount Airy, NC			
Corn	141	141	154
Cotton	776	773	835
Soybeans	47	45	50
Wheat	42	41	48
Bridgeville, DE			
Corn	122	110	118
Soybeans	36	29	36
Wheat	51	48	54
Davis, CA			
Cotton	1014	1129	1073
Wheat	85	86	84
Corpus Christi, TX			
Corn	137	175	144
Cotton	544	708	576
Sorghum	67	87	72
Soybeans	26	32	26

Figure 1

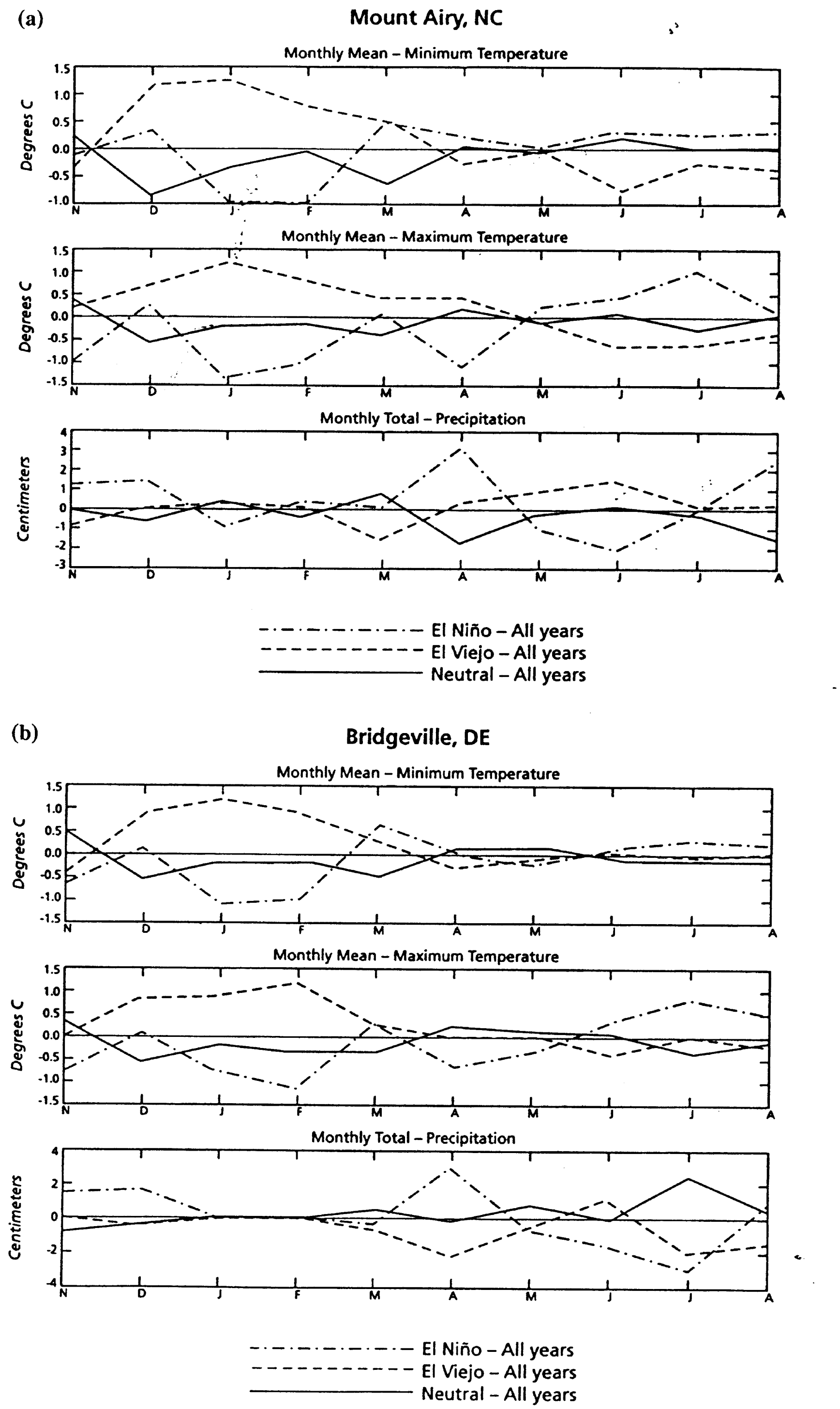
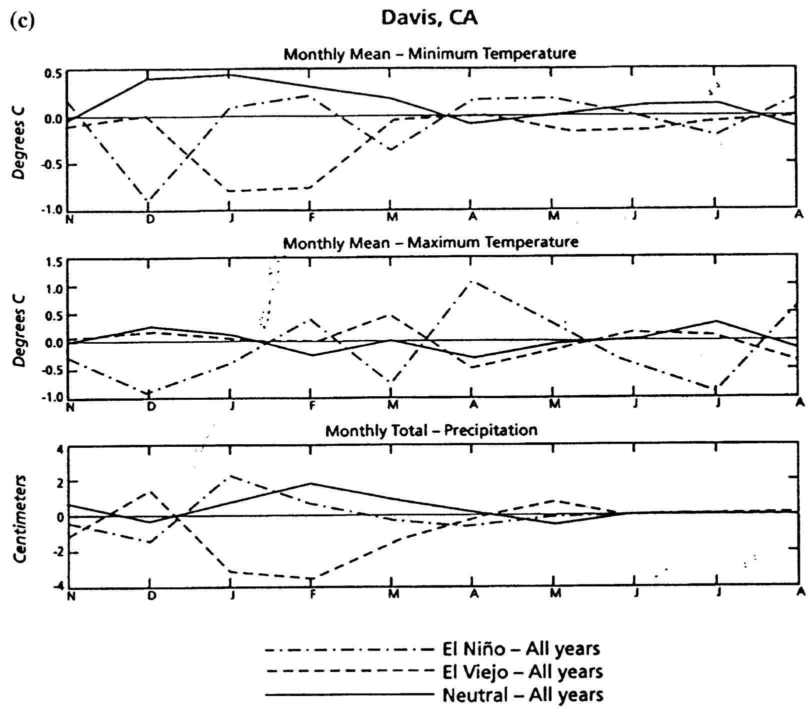


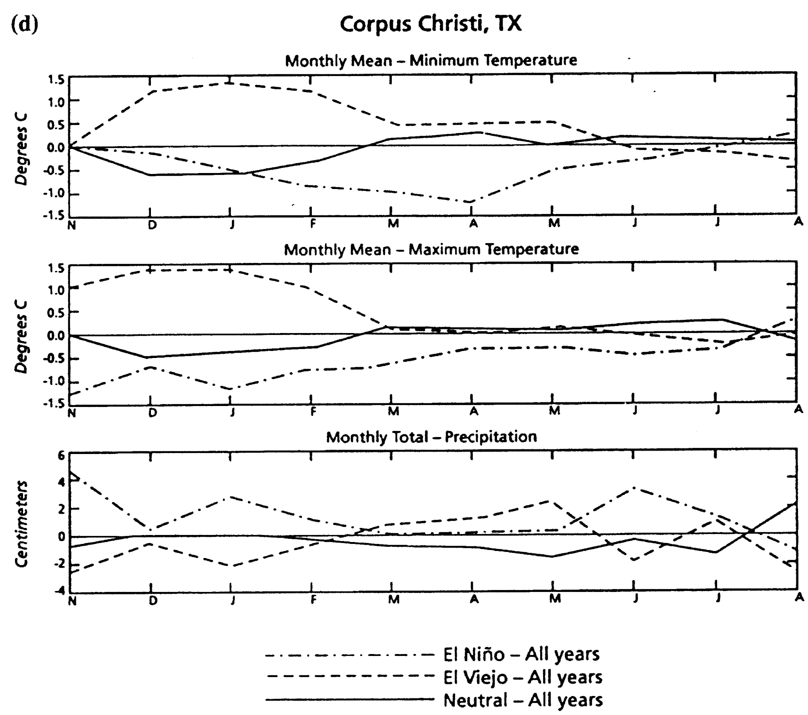
Figure 1a–b.

Figure 2

(c)


Davis, CA
Monthly Mean – Minimum Temperature
Degrees C
0.5
0.0
-0.5
-1.0
N D J F M A M J J A
Monthly Mean – Maximum Temperature
Degrees C
1.5
1.0
0.5
0.0
-0.5
-1.0
N D J F M A M J J A
Monthly Total – Precipitation
Centimeters
4
2
0
-2
-4
N D J F M A M J J A
El Niño – All years
El Viejo – All years
Neutral – All years

(d)


Corpus Christi, TX
Monthly Mean – Minimum Temperature
Degrees C
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
N D J F M A M J J A
Monthly Mean – Maximum Temperature
Degrees C
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
N D J F M A M J J A
Monthly Total – Precipitation
Centimeters
6
4
2
0
-2
-4
N D J F M A M J J A
El Niño – All years
El Viejo – All years
Neutral – All years

suited for this study.

The EPIC model estimates crop yield based on total biomass produced and a harvest index. Biomass and the harvest index increase through the growing season as a function of heat units. The harvest index may be reduced by high temperature, low solar radiation, or water stress during critical crop stages. Biomass may be reduced by water, temperature, and aeration stress and also by nitrogen and phosphorus stress.

The plant growth model in EPIC has been tested throughout the U.S. and in several other countries (Steiner et al., 1987; Williams et al., 1989; Bryant et al., 1992; Kiniry et al., 1995). The most comprehensive validation study was conducted by Williams et al. (1989). In that study, the model was tested for six crop species at 20 U.S. and 15 foreign locations with considerable variation in weather and soil characteristics. In all cases, mean simulated yield was within 7% of measured yield. Other studies found similar results.

The yield results for the stations shown in Figure 1 are given in Table III. Yield differences among summer crops were due mainly to differences in water stress. For example, corn in Mount Airy, NC and Bridgeville, DE suffered fewer days of summer water stress in El Viejo years than in El Niño and nonevent years. In contrast, the enhancement of growing conditions at Corpus Christi, TX during El Niño years was due to higher crop-available water in the spring months. Winter wheat yields are more affected by temperature stress than by water stress. For example, higher winter wheat yields during El Viejo years were due mainly to reduced winter temperature stress.

Decisionmaking and the Value of Prediction

Under the scenario considered in this paper, the climatological implications of an ENSO prediction are used to formulate a prediction of crop yields. The prediction of yields is then used by farmers to optimize cropping patterns. The way in which farmers use this information can be formalized in terms of Bayesian decision theory (Kite-Powell and Solow, 1994). This formalization is outlined in this section.

Let *a* denote a particular cropping pattern and let the random variable *S* denote the ENSO phase. The possible values of *S* are *E* (El Niño), *V* (El Viejo), and *N* (nonevent). Let *s* denote a realization of *S* and let *B(a| s)* be the profit for cropping pattern *a* if the realized ENSO phase is *s*. In the absence of an ENSO phase prediction, the expected profit for *a is:*

$$E(B(a)) = \sum_s B(a|s)\pi(s) \qquad (1)$$

where $\pi(s)$ is the probability that $S = s$.

The optimal cropping pattern a^* maximizes *E(b(a))*. Note that, in the absence of an ENSO phase prediction, the farmer optimizes cropping pattern over long-run average climatic conditions. In particular, a^* does not change from year to year. On the other hand, crop production in a particular year resulting from cropping pattern a^* depends on the realized ENSO phase in that year.

For a given ENSO phase *s*, the economy-wide supply for each crop resulting from optimal cropping patterns of each farmer in all regions can be found using a model capturing both farmers' decisions across all production regions and the demand for each crop. Let $T_1(s)$ be the economic surplus arising from the aggregate supply curves - that is, from supplies summed across all farmers in all regions. In the absence of an ENSO phase prediction, the expected economic surplus is given by:

$$T_1 = \sum_s T_1(s)\pi(s) \qquad (2)$$

Suppose now that an annual ENSO phase prediction is issued prior to the planting season. Let the random variable *X* denote the predicted phase and let *x* denote a realization of *X*. As with *S*, the possible values of *X* are *E*, *V*, and *N*. Although only categorical predictions were considered in this study, the same general approach could be applied to probabilistic predictions. Suppose that the ENSO phase prediction *X* in a particular year is *x*. The farmer uses this prediction to update the probability distribution of *S* according to Bayes's Theorem:

$$p(s|x)=p(x|s)\pi(s) / p(x) \qquad (3)$$

where $p(s|x)$ is the probability that $S=s$ given $X=x$,

$p(x|s)$ is the probability that X=x given S=s, and:

$$p(x)=prob(X=x)$$
$$= \sum_s p(x|s)\pi(s) \quad (4)$$

The likelihood $p(x|s)$ is a nonstandard measure of prediction skill. For a perfect prediction

$$p(x|s)=1 \quad \text{if } s = x$$
$$0 \quad \text{otherwise} \quad (5)$$

in which case:

$$p(s|x)=1 \quad \text{if } s = x$$

Table IV

Hypothetical likelihoods $p(X|S)$ for modest and high skill predictions

	Modest		
	$S = E$	$S = V$	$S = N$
$X = E$	0.60	0.15	0.20
$X = V$	0.15	0.60	0.20
$X = N$	0.25	0.25	0.60
	High		
	$S = E$	$S = V$	$S = N$
$X = E$	0.80	0.05	0.10
$X = V$	0.05	0.80	0.10
$X = N$	0.15	0.15	0.80

Table V

Posterior probabilities $p(S|X)$ for modest and high skill predictions

	Modest		
	$S = E$	$S = V$	$S = N$
$X = E$	0.46	0.15	0.39
$X = V$	0.11	0.54	0.35
$X = N$	0.12	0.15	0.73
	High		
	$S = E$	$S = V$	$S = N$
$X = E$	0.68	0.06	0.26
$X = V$	0.04	0.74	0.22
$X = N$	0.05	0.07	0.88

Table VI

Expected economic value of ENSO prediction ($ million per year)

Skill	Expected value
Modest	240
High	266
Perfect	323

0 otherwise (6)

In contrast, for a completely uninformative prediction, $p(x|s) = {}^1/_3$ for each s, so that $p(s|x) = \pi(s)$.

The individual farmer behaves as before, choosing the optimal cropping pattern $a^*(x)$ to maximize expected profit:

$$E(B(a)|x) = \sum_s B(a|s)p(s|x) \quad (7)$$

Note that, by averaging over $p(s|x)$ in Equation (7), the farmer is taking account of the possibility of incorrect phase prediction. Otherwise, the farmer would simply choose a to maximize $B(a|x)$.

The optimal cropping pattern $a^*(x)$ now depends on the realized ENSO phase prediction x. Let $T_2(x|s)$ be the economic surplus at the national level if $X = x$ and $S = s$. The conditional expected surplus given $X = x$ is found by averaging over the conditional distribution of S given $X = x$:

$$T_2(x) = \sum_s T_2(x|s)p(s|x) \quad (8)$$

and the unconditional expected surplus is:

$$T_2 = \sum_x T_2(x)p(x) \quad (9)$$

Finally, the value of the ENSO phase prediction is given by $T_2 - T_1$. The same approach can be used to assess the value of an improvement in—as opposed to the establishment of—an ENSO phase prediction.

It is important to stress that the value of ENSO prediction is an average or long-term concept. In a particular year, an incorrect prediction may lead to a loss. However, on average—or equivalently, over time—the use of the prediction will lead to an increase in profits.

Implementation and Results

To implement the Bayesian approach outlined in the previous section, it is necessary to specify prior probabilities of the ENSO phases and the likelihood function of the prediction scheme. In the study described here, the prior probability $p(s)$ was taken to be the relative frequency of s in Table I, so that:

$\pi(e) = 0.23 \qquad \pi(V) = 0.30 \qquad \pi(N) = 0.47$

As noted above, the likelihood function is a nonstandard measure of prediction skill. In the present study, three hypothetical levels of prediction skill—modest, high, and perfect—were considered. In related work, we are attempting to estimate the likelihood function of a simple, model-based ENSO prediction scheme (A. R. Solow and M. Cane, in preparation). The likelihood function for perfect prediction is given in the previous section. Those corresponding to modest and high skill predictions are given in Table IV. Using the prior probabilities given above, these likelihoods are converted into the posterior probabilities given in Table V.

For given posterior probabilities, an economic model called SPRASM was used to calculate expected surplus. This model is a stochastic programming version of the Agricultural Sector Model (ASM) that was used in the earlier study (Chang and McCarl, 1992). The ASM provides estimates of the changes in prices and quantities of agricultural products, and corresponding changes in economic surplus, due to changes in yields. This model was validated by solving for prices and quantities using 1992 yield data. The solutions were all within 2% of actual 1992 quantities and 5% of actual 1992 prices. Further details of this general approach to model validation are given in Fajardo et al. (1981). The incorporation of a stochastic component based on discrete stochastic programming (Lambert et al., 1995) provides a convenient and powerful way to capture decisionmaking under uncertainty. Under the combined model, farmers maximize expected profit subject to a market clearing condition and a set of resource constraints, while consumers utilize agricultural products with knowledge of prices. Again, it is important to stress that, under the decisionmaking component of this model, farmers take into account the possibility of incorrect phase predication as outlined in the previous section.

The results of the study are summarized in Table VI. These values, measured in 1995 dollars, are larger than those from the previous study. This increase is due, in part, to the larger geographic scope and the greater coverage of agricultural activities. However, due to the refinements of data and procedures in the present study, a direct comparison is not strictly possible. The annual values given in Table VI represent recurring gains to society. Assuming that future benefits are discounted at an annual rate of 6%, the net present value to the agricultural sector of a high skill ENSO prediction operating over 10 years is around $2 billion.

In interpreting the results in Table VI, it is important to distinguish between the economic value of unproved ENSO prediction and the economic impacts of a particular ENSO phase. For example, in this study, the economic surplus associated with a single El Niño year is approximately $2.5 billion less than that associated with a nonevent year. However, even with a perfect prediction, all of the negative effects (such as yield reductions) cannot be avoided, so that the value of predicting this event perfectly is considerably less.

Discussion

The study described here and in the earlier report represents the first systematic attempt to assess the economic value of ENSO prediction for a major sector of the U.S. economy. Although earlier attempts have been made (e.g., O'Brien, 1993), they have been based on *ad hoc* methods, rather than on a model of economic decisionmaking. The study described here documents the existence of ENSO signals in regional climate in the U.S. and identifies their consequences for crop yields. Advanced knowledge of these yield differences has potential value for farmers. The results of this study confirm the preliminary findings of the earlier study that ENSO prediction has substantial economic value to U.S. agriculture. While the specific results presented here seem reasonable, we believe that the main contribution of this paper is the description of a rigorous approach to assessing the value of long-range weather prediction. In implementing this approach, it is not necessary to use the EPIC model or the SPRASM model. Different or more elaborate models can be used. Incidentally, the same general approach can be used to assess the value of prediction to other sectors of the economy.

Turning to the specific results of this study, while the values in Table VI are substantial—particularly compared to the cost of ENSO prediction itself — they represent only around 1-2% of the net income of U.S. farmers. This may seem low, in light of the publicized effects of ENSO. There are features of the study that tend to underestimate the value of ENSO prediction to agriculture. For example, only cropping decisions were allowed to respond to ENSO prediction. No provision was made for other kinds of adjustments, such as alterations in inputs (e.g., fertilizers) or harvesting decisions. Also, some valuable vegetable and perennial crops were omitted from the analysis due to lack of information about potential yield effects. On the other hand, the study assumed that all farmers respond optimally to ENSO prediction. Failure of this assumption would lead to an overestimation of the value of ENSO prediction.

In addition to the technical problems associated with this kind of empirical analysis, the value of ENSO prediction to any sector is limited in two important ways. First, substantial climate variability remains within ENSO phases, particularly on the regional scale. To put it another way, even perfect ENSO prediction is far from perfect climate prediction. Second, as noted, the value of

ENSO prediction is limited by the capacity of decisionmakers to respond to the prediction. In almost all cases, this capacity will fall far short of avoiding all losses due to inclement climate.

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The Value of El Niño Forecasts in Agricultural Commodity Markets: The Case of U.S. Corn Storage[1]

Kevin McNew

Executive Summary

No other sector of the U.S. economy likely faces more of an impact from weather conditions than does the agricultural sector. The vagaries of weather can lead to substantial losses in agricultural crop production. For example, after a major drought impacted the Midwest in 1988, average U.S. corn yields were reduced by 40 percent. Such a sizable production shortfall can create problems because corn, like many other agricultural crops, is produced only once a year making it impossible to circumvent the shortage for a significant amount of time.

One way that production shortfalls can be buffered is through stockpiling, where commodities are stored from one year to the next. By having commodity reserves, the economy can partially offset the problems associated with inadequate supplies resulting from weather impacts. Storage of commodity reserves, however, is a limited buffer against production problems because stocks are not always held in the quantities needed to cover significant production shortfalls. For example, U.S. corn stocks are usually 10 to 20 percent of total U.S. production, but it is not unusual to have production shortfalls of 30 to 40 percent in a given year.

Why are commodities stockpiled in smaller quantities than needed to cover a potential production shortfall? The first reason is the significant costs associated with storing commodities. For the entire U.S. corn market, this cost can range from $250 to $500 million depending on how much is stored in a given year. The second reason is the possibility that the following year could lead to abundant production. If so, then the costly storage of commodity reserves would lead to even more supply than is needed. Therefore, the ability to predict weather patterns, and ultimately crop production a year in advance should improve the efficiency of storage reserves as a buffer. With better forecasts, this should lead to lower storage costs, which would benefit both U.S. farmers and consumers. If accurate one-year weather forecasts could be developed, then the economy could accumulate commodity reserves in anticipation of years when production would be unusually low and release stockpiles in years when abundant production is expected.

This research estimates the value of improved weather forecast information by considering how improvements in forecasting the El Niño-Southern Oscillation (ENSO) phase would be valued in the U.S. corn market. ENSO is a disruption of the ocean-atmospheric system in the tropical Pacific. It can be best understood as an oscillation between a warm and cold state, popularly known as El Niño and La Niña, respectively. These phases vary in duration but typically persist for 12 to 18 months. During the warm and cold episodes the normal pattern of tropical precipitation becomes disrupted and weather patterns are altered on a global scale. The ability to predict ENSO events is, therefore, of considerable public interest and a number of researchers have ad-

[1]The complete study can be obtained from Prof. McNew by e-mail at kmcnew@arec.umd.edu.

vanced the state of ENSO prediction. For example, it is not uncommon to find ENSO forecast models with a 70 percent accuracy rate for one year in advance. While there still exists the potential to improve ENSO forecasting accuracy, the ability to do so may require significant outlays by the Federal government and agencies involved in climatology research. Whether such improvements are warranted (and at what costs) depends on the value that economies derive from improved forecasts.

The results of this study are based on historical data from 1961 to 1996 and indicate that the El Niño phase tends to be associated with a larger than normal U.S. corn yield while the La Niña phase corresponds with a smaller than normal U.S. corn yield. Both events cause roughly a 4.6 percent deviation from normal yield levels. If these ENSO events could be perfectly predicted one year in advance, then U.S. corn stocks would decline by 8 percent in the long run. This would benefit both U.S. farmers and consumers. By having perfectly accurate ENSO forecasts, the benefit to both groups would total nearly $240 million on an annual basis.

The Value of Improved ENSO Forecasts

A Preliminary Assessment of the Effects on Fisheries in the Pacific Northwest[1]

Richard M. Adams, Christopher J. Costello, Stephen Polasky, David Sampson, Andrew Solow

Executive Summary

The El Niño Southern Oscillation is the largest source of interannual variability in the global climate system. The capability to make predictions of ENSO is already in place and is likely to improve in coming years. Extreme phases of this phenomenon, called El Niño events, are associated with climatic effects that have economic consequences in sectors such as agriculture, energy, and fisheries. Fluctuations, and extreme interannual variability in stock sizes of some U.S. Pacific fisheries, such as the coho salmon *(Oncorhynchus kisutch)* fishery, have been attributed, in part, to El Niño.

Historically, the Pacific Northwest coho fishery is thought to have been strongly influenced by El Niño events. Over the past 15 years such events are believed to be partly responsible for recent closures of both the commercial and recreational coho fisheries. Accurate short-term predictions of ENSO events, and associated variations in stock sizes, are hypothesized to have value to society insofar as they are incorporated into management regimes.

The overall objective to this analysis is assess the value of improved ocean/climate forecasts to marine fisheries in a stochastic, dynamic setting. Specific objectives include:

- development of a general modeling framework for assessing the value of improved forecasts and
- application of the model to valuing improved (more accurate) consecutive, one-year ENSO forecasts in the coho fishery.

To achieve these objectives, a bioeconomic model of coho salmon is developed, incorporating data and models from biology, climatology, economics, and oceanography. The bioeconomic model is framed as a stochastic decision making problem. Using Bayesian statistical techniques and a Monte Carlo analysis, the expected value of the coho fishery is estimated under the set of possible forecast state/true state combination. The value of information is extracted from these simulation optimizations.

The first step in this procedure involves constructing an economic model which includes decisions made under uncertainty. This model captures what are deemed the most relevant components of economic value (consumer plus producer surplus) in the coho fishery. These changes in economic surplus result from altered interannual management of the coho fishery. Based on estimation from previously published studies, in conjunction with data from various management agencies, demand estimates for charter ocean recreational, private ocean recreational, and in-stream angling are developed for use in the economic model. A social goal of maintaining viable wild salmon is incorporated using an existence value demand curve for wild fish. Finally, producer quasi-rents accruing to

[1]Subsequently published as "The Value of El Niño Forecasts in the Management of Salmon: A Stochastic Dynamic Approach", *American Journal of Agricultural Economics,* 1998, Vol. 80; pp. 765-777. This work, and a subsequent analysis, "The Value of Lengthening the ENSO Forecast Time-Frame: Case of the Pacific Coho Salmon Fishery," was jointed supported by NOAA's Office of Global Programs, and the Chief Economist.

commercial fishery and charter boat operators, less hatchery production costs, are estimated.

The economic model is then integrated with a biological model of coho salmon production with parameters stochastically determined by the ENSO phase. The ENSO phase is modeled as a random variable with three phases of occurrence with known historical probabilities; normal, weak El Niño, and strong El Niño. Each phase effects the life-history of coho salmon differently, but, in general, effects of El Niño on coho salmon in the Northeast Pacific include increased mortality, reduced fecundity, and reduced average weight. To create the assessment framework, a nonlinear spawner-recruit curve (Ricker model) is employed along with stochastic mortality, fecundity, and average weight variables. In this model, hatchery production is limited by a density dependent ocean mortality term which reduces survival of fish in the ocean as population density increases. The full stochastic bioeconomic decision model is employed to map out optimal management, and associated expected net present value of the coho fishery, under five models of varying forecast accuracy. Control variables, which the model chooses at each optimization stage, include harvest, hatchery production (for release the next time period), and hatchery smolt releases. The General Algebraic Modeling System (GAMS) and the Minos 5 nonlinear programming algorithm are used to solve this dynamic programming problem.

At the optimization stage, the model selects the most appropriate management (to maximize the net present value of the coho fishery) in any year given the current population level and prediction of future ENSO phases. However, calculating the value of information involves one more step in the analysis. The value of an improved forecast is the difference in the expected value of the objective function (the value of the Pacific Northwest coho fishery) with and without that forecast.

A base case must be identified from which to compare these values. The base case model involving the least accurate forecast (and subsequent management) is the naïve information model where fishery managers ignore the possibility of normal or weak events. This simplistic base case is probably unrealistic in that managers are aware of the effects of El Niño, and even without a forecast, probably exercise some “hedging” behavior to mitigate the effects of a strong ENSO event. Complexity of current stock predictors and management of the coho fishery prevents precise modeling of ENSO information as currently employed in management of the coho fishery. As an alternative to the naïve case, we use a “Certainty Equivalence” case, in which the manager assumes expected (or average) El Niño conditions for every future year. Value of information estimates reported in this summary employ this case as the basis for comparison.

Finally, an appropriate planning horizon must be identified over which the information will be valued. Results in the text are presented in functional forms, allowing the evaluation of forecast improvements over any planning horizon. For the purposes of this summary, a 50 year planning horizon is assumed.

Two models of enhanced ENSO forecasts are evaluated here. The first improved forecast assumes a posterior distribution halfway between the perfect and prior information cases. That is, the information in this model is halfway between guessing (based on historical frequencies of occurrence) and knowing the next year’s ENSO phase with perfect certainty. The value of developing the improved forecast, and incorporating it into management of the coho fishery on an annual basis is approximately $5.3 million over a 50 year planning horizon. This is roughly equal to $250,000 annually.

The second model of enhanced information is the perfect, one-year forecast. It is expected that this model will yield a significantly higher value estimate than the other, less accurate, forecasts. In fact, the value of a perfect, one-year ENSO forecast is approximately $19.4 million over a 50 year planning horizon, approximately $900,000 per year on average. This is equal to roughly two to three percent of the annual value of the fishery, as predicted by this model.

Although not a primary objective of this analysis, estimates of appropriate management actions in the face of an accurate ENSO forecast can be gleaned from model output. Specifically, when an El Niño is accurately forecast, harvest in the present period should decrease slightly, hatchery smolt releases should increase, and wild spawner escapement should decrease. This suggested shift from wild to hatchery production in times of poor ocean productivity is best understood by recognizing that wild fish are affected by El Niño throughout their life cycle, while hatchery fish are only affected for about one year.-- Model simulations also indicate that as a general rule, hatchery production should be decreased from recent average levels, perhaps by as much as 75 percent.

When an accurate forecast of ENSO is not available, the most appropriate management action involves "hedging" by managing based on the historical average ENSO event. This involves harvesting close to historical averages (approximately two million fish per year), releasing low numbers of hatchery fish (approximately eight million smolts per year), and allocating high numbers of wild spawners to escape (approximately 400,000—almost twice the current escapement target, but close to historical levels).

Value of information analyses will likely play a critical role in future research as agencies determine where to allocate research and development funding for large-scale data gathering and monitoring projects. With specific regard to fishery issues, analyses such as this can provide insight into the complex task of managing anadromous fish stocks. The results reported here demonstrate that improving the accuracy of the one-year ENSO forecast would be valuable in the management of the Pacific Northwest coho salmon fishery.

Cost Benefit Analysis of TOGA and the ENSO Observing System

Peter G. Sassone and Rodney F. Weiher[1]

R&D programs intended to develop climate prediction capabilities are costly. But if they are successful, they yield continuing economic benefits. However, because such benefits are difficult for private companies to capture, it falls to the public sector to pursue them. Public sector decision makers, before funding climate research programs, must be convinced that such programs serve the public interest, i.e., that their economic benefits exceed their economic costs. The purpose of this paper is to shed some light on that issue. Specifically, we construct a cost benefit analysis of the recently completed TOGA (Tropical Ocean Global Atmosphere) program. TOGA, a successful 10 year international scientific effort to understand and model the ENSO (El Niño / Southern Oscillation) phenomenon, has led to models which are capable of predicting ENSO events a year or so in advance. In our cost benefit analysis, we used estimates of the benefits of climate forecasts to the U.S. agricultural sector, the actual historical and the estimated future costs (to the U.S.) of the research, development and operationalization that climate forecast system, and a 36 case sensitivity analysis. Our results indicate that TOGA will provide a real economic return on investment to the U.S. of at least 13 percent to 26 percent, depending on the assumptions made in the analysis. This is substantially in excess of the hurdle rate of 7 percent usually used by the federal government. We conclude that the TOGA program was a sound use of public resources, and that additional funding of climate forecasting R&D efforts (at both the national and international levels) merits serious consideration.

The Economics of Climate Forecasts

Climate forecasts are *public goods*. A public good, as defined by economists, has two key characteristics: non-rivalry and non-excludability. Non-rivalry means that one person's consumption of the good or service does not diminish the amount of that good or service available for others' consumption. Non-excludability means that once the good is provided for anyone, it is readily and freely available to anyone else. In other words, it is difficult or impossible to exclude anyone from partaking of the good, once it's made available to anyone. Economists often cite national defense and clean air as examples of public goods. A climate forecast, because it is non-rival and nonexcludable, is also a public good.

The concept of a public good is important because it explains how a good or service may be highly valued[2] by the members of society and, yet, why private sector firms would be unwilling to produce it. This unwillingness is a simple consequence of non-excludability: if a firm can't prevent people from consuming the good without their paying for it, then many people won't pay (or at least would underpay), and the firm would not be able to recover its costs. In other words, in the case of public goods, there is a divergence between

[1] Extracted from *Operational Oceanography: The Challenge for European Cooperation;* J.H. Stel, ed. Elsevier Oceanography Series, 62; 1997, pp. 36-50.

the private and the social return on the investment required to produce the good.[3] The social return on the investment may be substantially greater than the private return. Economists recognize, therefore, that an important role of government—even in a market based economy—is the provision of certain public goods.

However, all goods that satisfy the criteria of being public goods do not merit public funding. It is not difficult to identify some public goods whose costs exceed their value to society. For example, nightly fireworks shows over the mall in Washington, DC would qualify as public goods (being both non-rival and nonexcludable), yet the social value of those nightly displays surely would be less than their cost. We can conclude that only those public goods which also pass the cost benefit test should be provided by government. The cost benefit test is that the value of the benefits to society (of the public good) should exceed its costs to society.

In some cases, it is relatively straightforward to estimate the benefits and costs of government programs, and in other cases it is quite difficult. Usually, when difficulties are encountered, it is the benefits that are the more problematic. It's important to recognize, however, that difficulty in quantifying benefits (or costs) does not render those effects any less real.

In the post-WWII era, much research and development came to be recognized as a public good, and much R&D consequently was supported by the federal government through grants and contracts with universities and private research organizations, and through the establishment of federal research units. Early in that period, the cost benefit test (while often recognized) was not widely demanded or applied by government decision makers. Beginning in the Reagan era, cost benefit analyses became more widely mandated; and in the fiscally conservative '90s, the pressure to "cost-justify" government expenditures has increased. Today, while climate research and forecasting programs are widely recognized as public goods, the costs and benefits of those programs are subject to increasing scrutiny. Indeed, there is widespread concern in the scientific community that such programs will likely not receive significant future funding unless there is compelling economic justification.

Climate Research Programs

Climate research has been funded, on a small scale, by the federal government at least since the DOT's Climatic Impact Assessment Program (CIAP) and the NSF's NORPAX program of the early '70s.[4] In 1984, the U.S. government joined with a number of other countries in the ten year TOGA (Tropical Ocean Global Atmosphere) program, which focused on understanding ENSO events. ENSO (El Niño/Southern Oscillation) refers to quasi-periodic climate episodes originating in the tropical Pacific, and affecting weather patterns in South and Central America, as well as in the southern U.S.[5] These climate episodes, with irregular annual periodicity, sometimes bring warmer and wetter weather (El Niño), sometimes colder and drier weather (Southern Oscillation or La Niña), and sometimes "normal" weather. The variation in climate is sufficiently dramatic as to cause widespread flooding in some years and drought in others. The breakthrough in understanding the ENSO phenomenon was made in 1969 by Norwegian meteorologist, Jacob Bjerknes. He recognized that the ENSO cycle was driven by the interaction of the atmosphere and the ocean in the tropical Pacific, and that models accounting for this interaction could predict ENSO events. The TOGA program's objectives were:

1. To gain a description of the tropical oceans and the global atmosphere as a time dependent system, to determine the extent to which this system is predictable on time scales of months to years, and to understand the mechanisms and processes underlying that predictability
2. To study the feasibility of modeling the coupled ocean-atmosphere system for the purpose of predicting its variations on time scales of months to years; and
3. To provide the scientific background for designing an observational and data transmission system for operational prediction if this capability is demonstrated by coupled ocean-atmosphere models.

The TOGA Program is recognized among the scientific community as a major success.

Based on that research, there now exist at least several ENSO prediction systems that have demonstrated prediction skill at least a season in advance. Perhaps the currently most successful coupled ocean-atmosphere model is that of Zebiak and Cane, which has predicted several ENSO events at least a year in advance.[7] Based on TOGA research, in 1995 the National Weather Service began issuing seasonal average temperature and precipitation forecasts for the continental U.S. for overlapping 90-day periods, out to a year in advance. These forecasts are published in a new monthly NWS product, *Climate Outlook*. In addition, another new product, monthly Outlooks, (forecasts for 30-day periods) will soon be issued by the NWS.

Based on the demonstrated successes of the TOGA program, follow-on programs have been developed and proposed by the scientific community. These proposals fall into two categories: the operationalization of past research and the conduct of new research.

NOAA's plan for an Operational ENSO Observing System falls into the first category.[8] During its 1985-95 lifetime, TOGA was developed, operated and funded as a research program. The plan now is to evolve this research program into an operational program for collecting data and making routine ENSO forecasts. This would be a key contribution of the U.S. to the international scientific community's GOOS and GCOS programs, which were formally established in 1991 and 1992, respectively.

The GOALS program falls into the second category. It is envisioned as a 15 year research program building on the success of the TOGA program. "The plan calls for an expansion of observational, modeling, and process research to include the possible influences of the global upper oceans and time-varying land moisture, vegetation, snow, and sea ice."

The question faced by U.S. budget authorities regarding these and other proposed climate programs is whether the benefits exceed the costs. However, the determination of the costs and (especially) the benefits of climate programs is not an easy matter. While cost benefit analysis is a highly refined and widely accepted tool used frequently by economists to evaluate alternative public sector investments, there are certain characteristics of climate prediction investments which render them inherently more difficult (than conventional public investments such as roads, bridges, buildings) to assess. These characteristics include:

- Uncertainty about the ultimate actual costs of the programs.
- Uncertainty about the ultimate success of the proposed research. Unlike a project to build a road or a bridge (where there is virtual certainty that the project can be accomplished), projects to develop climate prediction models are not guaranteed to succeed. The research simply may not uncover the hoped-for correlations and regularities among the variables.
- Even if the science is successful, the actual benefits of a (correct) climate forecast for a given season will be contingent on the actual climate which occurs. That is, if the actual climate is extreme, and if it's correctly forecasted, the benefits will be greater than if the actual climate is normal (and it is correctly forecasted). Of course, the benefits in a cost benefit analysis must be estimated for many years into the future, and there's no way of knowing what seasonal climate patterns will actually occur so far in advance.
- Cost benefit analysis (CBA) carries out an economic comparison of a proposed public investment versus a baseline, that is, versus a scenario in which the proposed investment project is not carried out. The two scenarios are assumed to be alike in every other salient respect. (This is the celeris paribus assumption commonly used in economic analysis.) Thus, CBA inherently compares the incremental benefits in the project scenario (that is, the gains over the baseline) to the incremental costs in the project scenario (the costs in excess of those incurred in the baseline scenario). In the case of a climate project, because climate research has already advanced to the point of enabling climate forecasts (albeit imperfect ones), the baseline scenario must include a statement as to what forecast would be issued

absent the proposed project, and what the consequences of that forecast would be. This would be a highly speculative basis for a CBA.

- Finally, the behavioral responses to climate forecasts would have to be specified for both the baseline and the project scenarios. That is, the extent to which the forecasts will be "believed" and acted upon by the relevant economic sectors in the future would have to be specified. Today, there simply isn't a sound basis on which to make credible long term forecasts of those parameters.

The dilemma, then, is that a CBA of climate research is necessary to assist U.S. budget officials in making funding decisions, yet the construction of such a CBA is fraught with difficulties.

A workable way around this dilemma is to focus on the recently concluded TOGA program, and on the proposed operationalization of the climate forecasting capability developed under its aegis. That is, one can view TOGA along with a subsequent operationalized ENSO forecasting system as a single program - extending 10 years into the past and perhaps 15 - 20 years into the future. This CBA would ask whether that program is worthwhile. The analysis would be retrospective with regard to the R&D costs of TOGA and prospective with regard to the costs of the operationalized observing and forecasting system. The benefits would be the future value of the seasonal to interannual ENSO forecasts which would be provided by the system, along with any additional scientific benefits not captured as part of the value of improved forecasting. In what follows, we adopt the shorthand, TOGA/EOS, to stand for the combined TOGA program and NOAA's proposed ENSO Observing System.

This approach to a CBA, while not overcoming all of the problems mentioned previously, strikes a balance between tractability and pertinence. It's tractable because the TOGA portion of the program has already occurred, so its costs and scientific outcomes are known with certainty. The EOS portion of the program is in the near future, so its costs can be estimated with some degree of confidence. This approach to CBA is pertinent because it is an objective assessment of the economic value of an actual climate research program. As such, it provides some insight into the potential value of similar research programs. In a sense, the proposed climate research programs of today are where the TOGA program was in 1985: a climate research program with substantial potential benefits, but also with a great deal of uncertainty.

The Purpose of this Study

The purpose of this study is to address the benefits and costs of climate research programs, and thereby support government decision makers who have budget responsibility in this area. More specifically, our purpose is to present the results of a cost benefit evaluation of a combined TOGA/EOS. The CBA, described below, finds that a lower bound estimate of *the social real internal rate of return*[9] of the combined TOGA/EOS program ranges from approximately 13 percent to 26 percent, depending on the particular assumptions employed in the calculations.

The CBA Framework

The fundamental concept in CBA is the comparison of alternative scenarios (or time lines). The baseline scenario is what happens without the proposed policy or program. The alternative (or project) scenario is what happens with the proposed policy or program. The impact of the policy or program is the difference between the two scenarios. The goal of CBA is to adequately identify and quantify that difference in monetary terms. CBA is almost always motivated by an impending policy or program decision, and the CBA is best seen as a decision-aid.

Cost benefit analysis generally proceeds along the following lines. The first step is clearly to identify precisely the issue to be addressed. That is, for exactly what policy or program are we trying to estimate the benefits and costs? And exactly what is the baseline? As already discussed, in this case we've chosen to focus on the TOGA/EOS program.

The second step in a CBA is qualitatively to identify the benefits and costs. This is done by filling in the details associated with each scenario, and identifying where the scenarios coincide and where they diverge. Where the scenarios coincide, no further CBA consideration is required, because there is no difference between scenarios. Where the scenarios diverge, those differences must be explicitly identified.

The third step is to quantify in physical dimensions (person-years, tons, bushels, etc.) those identified costs and benefits. The fourth step is to estimate the monetary value of those quantified physical effects. This is usually conceptually straightforward when treating costs, but it is sometimes quite challenging when dealing with certain benefits. In fact, it is in the valuation of benefits that economic theory makes its most important contributions to cost benefit analysis. Finally, the last step is to aggregate the monetary effects over time using present value analysis, to perform relevant sensitivity calculations, and to summarize results and conclusions.

Because CBAs are usually prospective (forward-looking), there often is substantial uncertainty about the values of many variables relating to future costs and benefits. There are two principal ways of dealing with uncertainty in CBA. One technique is the use of sensitivity analysis. Assuming that net present value (NPV) is the criterion being used in the CBA, sensitivity analysis determines how responsive (sensitive) the calculated value of NPV is to changes in the uncertain variables. The goal is to determine whether the conclusion of the analysis (whether the proposed investment is/is not worthwhile) is substantially affected by different plausible values of those key variables. Sensitivity analysis can be done in a variety of ways, some more sophisticated than others. Perhaps the simplest approach is to vary one variable at a time (often from “best” case to “worst” case values) and calculate the corresponding values of NPV. A sophisticated approach is to construct probability density functions for each key variable, and then (usually through a Monte Carlo analysis) construct the probability density function for the project’s NPV. In this way, the probability that NPV exceeds 0, or is in one range or another, can be readily estimated.

The second technique for dealing with uncertainty is by constructing intentionally conservative estimates of costs and benefits, thereby insuring that the final calculations yield a lower bound estimate of the net benefits of the program.

In practice, the two techniques of sensitivity analysis and of using intentionally conservatively biased estimates of costs and benefits can be combined, as we have done in this analysis.

The CBA Model for Climate Research

Our approach is to carry out an analysis of the combined TOGA/EOS program using, as the costs of the program, the actual historical costs of TOGA along with the projected costs of the ENSO Observing System as proposed by NOAA. In the model, the benefits of TOGA/EOS are the projected “expected” benefits to the U.S. agricultural sector of annual ENSO forecasts. The costs and benefits are aggregated using present value analysis. Specifically, the internal rate of return (IRR) for the entire investment is calculated. IRR is a widely used, and intuitively appealing, summary measure of the economic value of an investment.[10]

The IRR is an especially useful summary measure of the value of TOGA/EOS because it is independent of where, in the time line of the project, the analysis is grounded. In other words, in using the IRR criterion, it doesn’t matter whether we carry out the calculations as though we were in 1985 and we were looking at the entire TOGA/EOS program unfolding into future; or whether we assume we’re in the year 2010 looking back at the entire program; or whether we’re in 1996 looking back at TOGA and forward to EOS. As long as we use the same annual cost and benefit values in each calculation, the resulting IRR will be the same whether viewed from 1985, 1996, or 2010.

For convenience, the annual values of costs, benefits and related calculations are organized in a spreadsheet and shown in Table 1. Columns A and B show the time index and the corresponding years relevant to the analysis. Note that 1995 is indexed as time period “0.”

Column C shows the TOGA-related costs incurred by federal government agencies in each year up to and including 1995. These agencies include NOAA, NSF, NASA, and ONR.

TABLE 1
COST BENEFIT ANALYSIS WORKSHEET

A	B	C	D	E	F	G	H	I	J	K	L
TIME INDEX	FISCALYEAR	U.S. Govt. TOGA-related current costs (000) from U.S. govt. budget documents	Annual estimated current cost of ship time not included elsewhere ($000)	Total current annual costs = govt cost + ship time	Implicit price deflator for federal nondefense purchases, 1987=100 [Source: BEA, 1995 estimated]	Factor to adjust current costs to 1995 dollars	Total pre-1995 costs expressed in 1995 dollars (000)	Estimated annual post-1995 costs of ENSO Observing System, in 1995 dollars (000)	Percent of agriculture decision makers using ENSO forecast	Estimated annual benefits to US agriculture of ENSO forecasts, in 1995 dollars (000)	Estimated annual net benefits in 1995 dollars (000)
parameter value:								$12,300		$240,000	
										$266,000	
formula:				C+D			G*E			J*(above)	K-H-I
-11	1984	$4,624		$4,624	91.3	1.47	$6,787				($6,787)
-10	1985	$6,041		$6,041	95.7	1.40	$8,459				($8,459)
-9	1986	$5,227		$5,227	98.6	1.36	$7,104				($7,104)
-8	1987	$16,615	$1,275	$17,890	100.0	1.34	$23,972				($23,972)
-7	1988	$17,276	$355	$17,631	101.4	1.32	$23,299				($23,299)
-6	1989	$12,595	$917	$13,512	107.3	1.25	$16,874				($16,874)
-5	1990	$20,910	$70	$20,980	112.0	1.20	$25,101				($25,101)
-4	1991	$32,185	$437	$32,622	116.9	1.15	$37,394				($37,394)
-3	1992	$35,700	$1,260	$36,960	120.2	1.11	$41,203				($41,203)
-2	1993	$30,925	$4,607	$35,532	124.7	1.07	$38,182				($38,182)
-1	1994	$30,170	$2,065	$32,235	130.5	1.03	$33,099				($33,099)
0	1995	$10,400	$1,058	$11,458	134.0	1.00	$11,458				($11,458)
sum		$222,668	$12,043	$234,711			$272,932				
1	1996							$12,300	50.00%	$120,000	$107,700
2	1997							$12,300	57.50%	$138,000	$125,700
3	1998							$12,300	65.00%	$156,000	$143,700
4	1999							$12,300	72.50%	$174,000	$161,700
5	2000							$12,300	80.00%	$192,000	$179,700
6	2001							$12,300	87.50%	$232,750	$220,450
7	2002							$12,300	95.00%	$252,700	$240,400
8	2003							$12,300	95.00%	$252,700	$240,400
9	2004							$12,300	95.00%	$252,700	$240,400
10	2005							$12,300	95.00%	$252,700	$240,400
11	2006							$12,300	95.00%	$252,700	$240,400
12	2007							$12,300	95.00%	$252,700	$240,400
13	2008							$12,300	95.00%	$252,700	$240,400
14	2009							$12,300	95.00%	$252,700	$240,400
15	2010							$12,300	95.00%	$252,700	$240,400
16	2011							$12,300	95.00%	$252,700	$240,400
17	2012							$12,300	95.00%	$252,700	$240,400
18	2013							$12,300	95.00%	$252,700	$240,400
19	2014							$12,300	95.00%	$252,700	$240,400
20	2015							$12,300	95.00%	$252,700	$240,400

Column D shows the cost of ship time (ships are used to deploy and tend buoys). Column E is the sum of C and D. Column F is the relative price index (for federal nondefense purchases). The index is anchored at 1987 (index = 100), and the index in each year is stated relative to 1987. For example, the value of 130.5 for 1994 means that a given bundle of goods purchased by the federal government in 1994 would cost 30.5 percent more than that same bundle would have cost in 1987. In other words, the effect of inflation was to increase the costs of goods to the government by 30.5 percent over the period 1987 to 1994. Using the price index allows us to remove the effect of inflation. For convenience, we adjust all costs to equivalent 1995 values. This is done by constructing in column G a new index anchored at 1995, and then multiplying each value in column E by that new index. Note that the new index (column G) is simply 134.0 (the 1995 price index in column F) divided by the column F index value for that particular year. For example, the 1984 index value in column G is 134.0 / 91.3 = 1.47. This means that costs incurred in 1984 can be converted to their equivalent 1995 value by multiplying them by 1.47. These equivalent costs of the TOGA program are shown in column H. Note that although the costs in column H are adjusted for inflation, they are not adjusted to account for the present value of those historical costs. The adjustment for present value, done through the internal rate of return calculation discussed below, takes account of the investment return that could have been earned on resources consumed in earlier years.

Turning now to the ENSO Observing System, current government planning documents indicate an expected annual cost of the system of $12.3 million. That value is shown in column I as the future annual cost, expressed in 1995 dollars.

For the purpose of this analysis, we use the estimates developed by Adams et al. of the social benefits related to the U.S. agricultural sector of improved ENSO forecasts.

These figures, discussed below, are a measure of the gain in consumers' and producers' surplus associated with improved information. At the top of column K of Table 1, the figures $244,000 and $266,000 are shown. These are the estimates produced by Adams et al. of the expected annual value (in 1995 dollars) of 60 percent and 80 percent skill levels (respectively) ENSO forecasts. These estimates assume that all farmers heed and act on the forecasts.

Because there is likely to be incomplete acceptance by farmers of ENSO forecasts, at least initially, we have built into the CBA model a "forecast acceptance curve." A range of forecast acceptance curves were used in the analysis, and are discussed below. The particular curve illustrated in Table I embodies the assumption that acceptance starts off at 50 percent level, and builds to a maximum of 95 percent over a six year period. The resulting dollar benefits, shown in column K, are the product of column J and either $240,000 or $266,000 (depending on the assumption made about the accuracy of the forecast system. Finally, column L shows the annual net benefits (benefits–costs) of the TOGA/EOS investment. Column L is calculated as columns K - H - 1. The internal rate of return calculation (technically, the real internal rate of return) is calculated from the values in column L, which show the annual flows of resource values either consumed or generated by the TOGA EOS program.

Measurement of Benefits

As mentioned above, in this study we have relied upon the results of a recent study by Adams et al. of the value to U.S. agriculture of alternative skill levels in forecasting ENSO events. This study (forthcoming) builds on methodology and results of a previous study by the same authors which focused on southeast U.S. agriculture.[11] The methodology employs a Bayesian "value of information" framework.

In their initial study, Adams et al. estimated the value of improved ENSO forecasts to southeastern U.S. agriculture as $145 million (for perfect forecasts) and $96 million (for 80 percent accurate forecasts). That initial research was recently modified and extended by Adams et al. to cover the entire U.S. agricultural sector. This latest study:

"evaluated the economic value of three forecast skill levels with regard to the three ENSO states. These forecast skill levels are 1) a modest forecast skill level of .6 probability (technically, .6 is the probability of a forecast of a specific ENSO phase, given that the phase occurs); 2) a forecast skill level (improvement) to .8 probability (a "high " skill level) and 3) a perfect forecast (probability of 1.0). These three skill levels and three states of nature frame the set of possible economic consequences (considered in the study). The economic consequences associated with all forecast skill-outcome (ENSO phases or states of nature) combinations are measured against a common base - the economic value of a "no-skill" forecast situation, where producers follow historical crop management decisions each year."[12]

The results of this latest study (which are not entirely comparable to the previous results) indicate that the annual value of perfect ENSO forecasts is $323 million, the value of high skill (80 percent accurate) forecasts is $266 million, and the value of modest skill (60 percent accurate) forecasts is $240 million. These figures are "expected" annual values, in 1995 dollars. The expected value is computed by assuming that El Niño, La Niña, and "normal" climate are each likely to occur in the future according to their actual historical relative frequencies, and that the forecast skill (60 percent, 80 percent, or 100 percent) is independent of the actual climate.

At the present time, the research of Adams et al. is the only work we could identify which has attempted to quantify—at the national level, and taking general equilibrium considerations into account—the economic value of ENSO forecasts. In the cost benefit analysis reported here, we have used the recent Adams et al. figures as the expected benefits of improved ENSO forecasts. By ignoring the benefits in economic sectors other than agriculture, we are understating the actual benefits—perhaps to a substantial extent.[13] Also, by ignoring any benefits which would accrue to other countries affected by ENSO events (e.g. in Central and South America), we are further understating total benefits.[14] Also, by using the Adams et al. 1995 values as the values for future years as well (effectively assuming a stagnate U.S. agricultural sector), benefits are further understated. Thus, we believe it is appropriate to interpret our results as lower bound estimates of the value of the TOGA/EOS program.

In order to deal further with the uncertainties in the analysis, four parameters were varied in our sensitivity analysis: the ENSO forecast skill level, the future time horizon, the rate of acceptance of ENSO forecasts by the agricultural sector, and the annual (future) cost of the ENSO Observing system (including the cost of generating and disseminating the forecasts). By varying these four parameters, 36 scenarios were generated and evaluated.

Results

Table 2 shows the results of our cost benefit evaluation of the 36 scenarios just mentioned. Note that the forecast skill level was allowed to assume 3 values: 60 percent accuracy, 80 percent accuracy, and a combination 60 percent/80 percent that allows for improvement in ENSO forecasting as more data are collected and models are refined. In 60 percent/80 percent case, we assumed that forecast skill improves from 60 percent to 80 percent after 5 years into the EOS program.

The time horizon over which future benefits are counted was set at two values: 10 years and 20 years. The ten year perspective is admittedly short, because we would expect that ENSO (and other climate phenomena) forecasts would continue to be made indefinitely into the future. The issue, from the CBA perspective, is how long into the future we can credibly associate the benefits of ENSO forecasts with the costs and results of the TOGA program. It is certainly conceivable that new climate theories and forecasting models may evolve, and such models may not stand directly on the foundation laid by TOGA. Thus, while it is admittedly difficult to pin down a "best" time horizon, 10 and 20 years may reasonably bound the contribution of TOGA.

Agriculture has become an increasingly sophisticated economic sector, highly dependent on technology and knowledge. Today, farmers routinely adopt new technologies, such as hybrid seed or new herbicides, pesticides and fertilizers.

Table 2
SUMMARY OF RESULTS

REAL IRR FOR TOGA/ENSO OBSERVING SYSTEM (FY84 TO FY05 OR FY16) FOR SELECTED PARAMETER VARIATIONS

CASE	FORECAST SKILL LEVEL	BENEFITS TIME HORIZON	RATE OF FORECAST ADOPTION	ANNUAL COST OF ENSO	REAL IRR
1	60%	10	SLOW	$12.3M	13.39%
2	60%	10	SLOW	$17.3M	12.87%
3	60%	10	MODERATE	$12.3M	19.60%
4	60%	10	MODERATE	$17.3M	19.14%
5	60%	10	IMMEDIATE	$12.3M	23.88%
6	60%	10	IMMEDIATE	$17.3M	22.93%
7	60%	20	SLOW	$12.3M	17.16%
8	60%	20	SLOW	$17.3M	16.78%
9	60%	20	MODERATE	$12.3M	21.62%
10	60%	20	MODERATE	$17.3M	21.22%
11	60%	20	IMMEDIATE	$12.3M	25.13%
12	60%	20	IMMEDIATE	$17.3M	24.26%
13	80%	10	SLOW	$12.3M	14.51%
14	80%	10	SLOW	$17.3M	14.03%
15	80%	10	MODERATE	$12.3M	20.75%
16	80%	10	MODERATE	$17.3M	20.42%
17	80%	10	IMMEDIATE	$12.3M	25.22%
18	80%	10	IMMEDIATE	$17.3M	24.29%
19	80%	20	SLOW	$12.3M	18.09%
20	80%	20	SLOW	$17.3M	17.74%
21	80%	20	MODERATE	$12.3M	22.63%
22	80%	20	MODERATE	$17.3M	22.35%
23	80%	20	IMMEDIATE	$12.3M	26.37%
24	80%	20	IMMEDIATE	$17.3M	25.51%
25	60%/80%	10	SLOW	$12.3M	14.06%
26	60%/80%	10	SLOW	$17.3M	13.57%
27	60%/80%	10	MODERATE	$12.3M	19.98%
28	60%/80%	10	MODERATE	$17.3M	19.64%
29	60%/80%	10	IMMEDIATE	$12.3M	23.57%
30	60%/80%	10	IMMEDIATE	$17.3M	23.30%
31	60%/80%	20	SLOW	$12.3M	17.81%
32	60%/80%	20	SLOW	$17.3M	17.45%
33	60%/80%	20	MODERATE	$12.3M	22.04%
34	60%/80%	20	MODERATE	$17.3M	21.75%
35	60%/80%	20	IMMEDIATE	$12.3 M	24.93%
36	60%/80%	20	IMMEDIATE	$17.3M	24.68%
AVERAGES:		15	MODERATE	$14.8M	20.35%
RANGES:	60% TO 80%	10 TO 20 YRS	SLOW TO IMMEDIATE	$12.3M TO $17.3M	12.87% TO 26.37%

Some research on the diffusion of new technology in the agricultural sector suggests that new technology becomes substantially absorbed into the industry over a period of less than a decade. While ENSO forecasts are a somewhat different kind of "technology" than farmers are accustomed to dealing with, we assumed here that the adoption and use of such forecasts by mainstream agriculture will not be remarkably different from farmers' adoption of other new technologies. Thus, for our sensitivity analysis, we posited three "ENSO forecast adoption" scenarios.

In one scenario, which we labeled the "SLOW" rate of forecast adoption, we assumed that initially only 10 percent of the agricultural sector heeds (and acts on) the forecast. In successive years, that percent grows to 20 percent, then 30 percent, etc.; finally peaking at 90 percent in the ninth year, and remaining at 90 percent thereafter.

In another scenario, which we labeled the "MODERATE" scenario, the initial acceptance is 50 percent, growing linearly to 95 percent over a six year period (and remaining at 95 percent thereafter). This is the scenario reflected in Table 1. Finally, as the most optimistic case, we assumed that there would be "IMMEDIATE" 95 percent acceptance.

Conclusions

The calculated real internal rate of return for the 36 scenarios of the combined TOGA EOS program is shown in the last column of Table 2. The real IRR values range from about 13 percent to 26 percent. The Office of Management and Budget recommends to federal agencies that such IRRs be compared to a hurdle rate of 7 percent.[15] The reasoning is that "(t)his rate approximates the marginal pre-tax rate of return of an average investment in the private sector in recent years." In other words, had resources not been absorbed by TOGA and (prospectively) the EOS, and if those resources had remained in the private sector, they could have been invested in private sector projects generating a real return of about 7 percent. Thus, the opportunity cost of the capital absorbed by the TOGA/EOS programs is 7 percent. We should, therefore, judge those programs economically worthwhile only if they generate returns to society at least as great as the cost (real 7 percent) they impose.[16]

By this criterion, the TOGA / OEFS program handily passes the CBA test. Importantly, the range of results produced by the sensitivity analysis (the 36 cases) falls entirely on the "up" side of the hurdle. Considering these results, and subject to the usual qualifications, we can be reasonably confident that the TOGA/EOS program represents sound use of society's resources.

Furthermore, it is clear from the analysis that if one focused solely on the prospective EOS program, accepting TOGA as a now sunk cost, its real IRR would be substantially higher than those values reported above. Thus, we can confidently conclude that the presently proposed ENSO Observing System, built on TOGA, is a worthwhile public investment.

Finally, as suggested above, one might say the proposed GOALS program today is where TOGA was in 1985—a promising but uncertain climate research program. Our results here suggest that climate research has measurable and substantial economic payback. That is a clear argument in favor of society's continuing a modest stream of investment in climate research.

Notes

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[2]Value is usually measured as informed and rational consumers' willingness and ability to pay for something, rather than going without it.

[3]Private return is the financial gain (profit) to firms producing and selling the product. Social return also includes those gains to consumers (willingness to pay in excess of actual payments) which are not appropriated by firms. This latter gain is called consumers' surplus.

[4]CIAP was a research effort, funded through the USDOT, to assess the climate impacts of a proposed fleet of supersonic transport (SST) aircraft. NORPAX (North Pacific Experiment) pioneered the use of expendable bathythermograph profiling from volunteer observing ships.

[5]There is some evidence of ENSO effects in Europe and Northern Africa, as well.

[6]National Research Council GOALS for Predicting Seasonal-to-Interannual Climate, Washington, DC 1994.

[7]Zebiak and Cane "A Model El Niño/Southern Oscillation" Mon. Wea. Rev. 115:2262-2278, 1987.

[8]Michael Johnson et al., Transition Plan Towards an Operational ENSO Observing System, NOAA, November 1995.

[9]Our terminology needs explanation. "Lower bound" means that we have used conservative estimates of costs and benefits so our results are likely not to overstate the value of the program. "Social" means we've included benefits to consumers as well as producers. "Real" means that in our analysis we have removed the effects of inflation. "Internal rate of return" is discussed below. " IRR is often used in evaluating financial investments, such as the purchase of securities.

[10]For example, a bond which costs $1000 and which pays the holder $100 per year in interest, and which then returns the principal of $1000 along with the final $100 interest payment has an IRR of 10 percent. Another way of interpreting the IRR is as that discount rate which, if used to calculate the net present value of the investment, would result in a value of $0. A project's calculated IRR should be compared with the opportunity cost of that investment (the rate of return that could be earned in the next best investment). Currently, OMB suggests a real value of 7 percent as the appropriate hurdle rate

[11]Adams et al., "Value of Improved Long-Range Weather Information," Contemporary Economic Policy, Vol. XIII, July 1995

[12]Personal communication between Adams and one of the authors.

[13]Research, sponsored by NOAA, is currently underway to quantify the value of climate forecasts in other climate sensitive sectors, such as hydroelectric power, natural gas, water management, and fisheries.

[14]Whether to include "spillover" benefits to other countries in a CBA depends on the perspective and purpose of the CBA. Certainly, a global CBA perspective—as discussed later in this report—would include those benefits.

[15]OMB Circular A-94 (revised), 10/29/92: Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs

[16]It's worth noting that even if society would have chosen to consume, rather than invest, the resources absorbed by the TOGA / EOS programs, the conclusion remains unchanged. This is because, in choosing to consume rather than accept a 7 percent real return, society reveals that present consumption is worth at least as much as the flow of future consumption that could be financed by the investment of those resources.

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