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# Market-Based Methods for Monetizing Uncertainty Reduction: A Case Study

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# About the Authors

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# Abstract

New measurement systems are often expensive and need a solid economic justification. Traditional tools based on the value of information are sometimes difficult to apply. When risks are traded in a market, it may be possible to use market instruments to monetize the reductions in uncertainty. This paper illustrates such market-based methods with a satellite system designed to reduce uncertainty in predicting soil moisture in the United States. Soil moisture is a key variable in managing agricultural production and predicting crop yields. Using data on corn and soybean futures, we find that a 30 percent reduction in the weather-related component of uncertainty in corn and soybean futures pricing yields a yearly US consumer surplus of $1.44 billion. The total present value of information from the satellite system for the United States—calculated with a 3 percent discount rate—is about $22 billion, assuming the system is in operation for 20 years. The global value of the improvements in weather forecasting could be $63 billion.

**Key words:** Value of Information, options pricing, SMAP, Bachelier formula, Black-Scholes-Merton model

**JEL Codes:** C02, C44, C58, D80, D81

# Contents

# 1. Introduction

As measurement systems become more complex and more costly, political leaders may become less engaged with science. The market makes resources available for technological innovation but, as often pointed out (e.g., Weatherhead et al. 2018; Archer 2016), resourcing the research on which innovation depends may be challenging. Fields like climate science—with studies that show obvious near- and medium-term impacts on human welfare but with little immediate market value—are underfunded. For example, world outlays for climate research amount to about 5 percent of the yearly profits of Exxon Mobil.[1] A key question for leveraging market forces to support more research is how to monetize reductions in uncertainty. This paper focuses on monetary value rather than on utility of social welfare generally.

Traditional value of information (VOI) theory (see, e.g., Lawrence 2012; Keisler et al. 2014) is very well-anchored in decision theory. However, traditional VOI techniques face several challenges in application. Baseline uncertainty, prior to costly measurements, must be quantified. A decision context also must be identified—in which uncertainty reduction can be parlayed into better decisions with higher expected values. Of the 252 VOI applications reviewed by Keisler et al., only 74 are applied to actual problems (2014, 8); more real applications have emerged since then (see, e.g., Cooke et al. 2017, 2015, 2013; Gradowska and Cooke 2013).

This paper explores a new approach based on options theory. The approach applies in cases where risks are traded on a market, and it can be used either ex ante or ex post. An ex ante (i.e., prospective) VOI study is an assessment of the economic value of an information-gathering mission conducted prior to mission completion. Typically, an ex ante assessment will be performed during the mission design and early operational phases to give a ballpark indication of the economic value that the mission could potentially harvest. In contrast, ex post (i.e., retrospective) studies quantify the economic value actually harvested after mission completion.

NASA's Soil Moisture Active Passive (SMAP) mission, launched in 2015, provides a workbench for monetizing future information. SMAP is an Earth-observing satellite that measures and maps the moisture and freeze/thaw states of soil on the planet, aiming to provide better data that can inform drought monitoring, flood prediction, and crop management among many other efforts. Agricultural risks are actively traded

[1] See Archer (2016), yearly global outlays for climate research are said to be $2 billion. Exxon's yearly profits are around $40 billion.

in large markets, thus rendering SMAP a good candidate for ex ante market-based monetization of uncertainty reduction.

Soil moisture strongly affects plant growth and agricultural productivity, especially during water shortages and droughts. Crop conditions shift quickly due to changes in soil moisture, temperature, fertilization, or disease. High-frequency, high-resolution geospatial data—especially during growing seasons—are critical for food security, assessments of crop yields, and informed decisionmaking in agricultural production and commodity markets.

Currently, no global *in situ* network exists for monitoring soil moisture. Predictions are model-based with relatively low resolution and large uncertainties. SMAP aims to dramatically improve model predictions. The technologies for model improvement are still under development—but tools for monetizing future reductions in uncertainty are needed now.

The present study focuses on the value that could be harvested by reducing uncertainty in US corn and soybean crop yields. This does not target the total value of the mission. We show that a 30 percent reduction in the weather-related uncertainty (standard deviation) in the price of US corn and soybeans is worth $1.44 billion per year. Similar computations could be done for other crops or, indeed, for any commodity with risks that are traded on the market. This provides a new line of attack for making the economic value of new information visible to policymakers and to the general public.

This paper is structured as follows: in Section 2, we discuss an introductory example of risk trading. Section 3 explains the risk quantification methodology based on options pricing. Section 4 explains the selection of a simplified option pricing formula for VOI analysis. Section 5 establishes the methodology for monetizing uncertainty reduction in weather predictions. In Section 6, we apply this methodology to illustrate VOI calculation assuming uncertainty reduction of the weather predictions by 30 percent. The final section draws conclusions; the Annex presents historical data.

# 2. Simple Example of Risk Trading

Markets have mechanisms for trading risks between those who will pay to remove a risk and those who will accept payment to assume that risk. An early example is the corn futures market. Farmers need to purchase seed corn before planting. Because the future price of seed corn is uncertain, farmers are willing to pay a premium in September to guarantee that they can purchase a given quantity of seed in April of the following year at a given price—the "strike price."[2] If the actual price in April is below the strike price, the seller of the futures option makes money as he can buy at the market and sell for a higher price to the farmer. If the actual price is above the strike price, the seller loses. In any event, the farmer purchases his seed corn at the price he anticipated in September. If no uncertainty existed in the future price of seed corn, there would simply be no futures market. If the April price were known with certainty to be within $0.50 per bushel of the September price, then the price of the futures option could not exceed $0.50 per bushel. As the uncertainty of the April price increases, so does the price of the futures option.

The idea of using options prices to value reductions in uncertainty depends on having pricing models that translate options prices into quantifications of uncertainty. Since the introduction of the corn futures markets, the market instruments for risk trading have expanded enormously. The following example introduces the simplest instruments in a more general setting.

[2] A futures contract is a legal agreement to buy or sell a particular **commodity** or asset at a predetermined price at a specified time in the future.

# 3. Risk Quantification Using Option Pricing

Suppose a family has a college savings of $50,000, and the savings will be needed in two years to cover tuition. At present, the $50,000 is invested in an exchange-traded fund (ETF) DIA that replicates the Dow Jones Index and should yield a similar return. Over the last eight years, the assets invested in DIA increased in value about 2.5 times (about 11.5 percent per year). The family has 200 shares of DIA. At the beginning of September 2018, the shares were traded at around $260 per share, thus the current market value of the investment is about $52,000. If the shares continue to grow at 11.5 percent per year, then by September 2020 the value will be about $65,000.

However, if the market goes down, the family may lose a critical fraction of savings meant to cover college tuition in two years. During two years, in April 2007 to April 2009, DIA shares dropped by 45 percent. The market value of this downside risk could be calculated as a value of a "European put option at-the-money" on DIA shares. This option gives the family the right, but not the obligation, to sell its shares at $260 per share on August 1, 2020. The put option contract costs $20 per share and the total cost to hedge the entire position is about $4,000. In case DIA value is below $260 per share on August 1, 2020, the family exercises the options contract and protects its savings. The family is exposed to risk with a market value of $4,000. There are many different types of options. For example, an "American put option at-the-money" allows the family to sell its DIA shares for $260 at any time prior to August 1, 2020. Options need not be "at-the-money" but may involve a strike price different from the current price.

Suppose our family also wants to make a down payment of $50,000 on a house in September 2020 and has a separate portfolio of shares of TFT[3]. The shares of TFT have about the same volatility as DIA, also with a hedging cost of $4,000. Hedging both positions would cost $8,000. However, since DIA and TFT are not completely correlated, it is quite possible that one option would be exercised in September 2020 but not the other. If the family shops around, they might find an options trader who would hedge both positions for $7,000. The options market provides many exotic and

[3] TFT is the iShares 20+ Year Treasury Bond ETF. The fund seeks to track the investment results of an index composed of US Treasury bonds with remaining maturities greater than 20 years (see: **https://www.ishares.com/us/products/239454/ishares-20-year-treasury-bond-etf**)

complex hedging strategies. For simplicity and because of the availability of market data, we do not further consider exotic strategies here.

To use options prices to value a reduction in uncertainty, we must relate the market value of the risk ($4,000 in the above example) to uncertainty in the underlying asset. This is accomplished by options pricing models relating the monetary risk to a measure of uncertainty called "volatility". Volatility is the standard deviation of the one-period percentage change in the price of the underlying asset. Given a pricing model and knowing the options price, we can back out the volatility of the underlying asset. A measure of volatility obtained in this way is called "implied volatility". Using reported data on option pricing, the implied volatility of DIA is about 14 percent (one-year volatility). In other words, if the price of the underlying at period one is $260, the $1\sigma$ confidence band for the price in the next period is $\$260\times(1\pm0.14)$ = ($223.6, $296.4); the $2\sigma$ confidence band is ($187.2, $332.8). Implied volatility can thus be related to the uncertainty distribution of the underlying asset.

We can now run this argument in the other direction. If we reduce the standard deviation of the underlying, we can compute the resulting reduction in the options price, and this translates to consumer surplus. If our family can buy off its risk for $2,000 instead of $4,000, it will have $2,000 to spend on other things. If the reduction of uncertainty is expressed as a reduction in the standard deviation of a risky asset, that will affect all types of options on that asset. There is no need to compute the price reduction of European, American, calls, puts, at-the-money, not at-the-money, etc.—as they are all functions of the volatility. For a prospective VOI study, it is sufficient to consider a simple European call option at-the-money and the total volume of trade in the underlying asset[4].

It is important to emphasize that the market is not prescient. The fact that the buyer and seller agree on the price of an option does not mean that the volatility implied by that price is correct. If the buyer and seller both believe that climate change is a hoax, they may trade options on climate-related risky assets at a very low price. If they believe there is a significant chance that climate damages will occur, they would trade such options at much higher prices. The market doesn't know which price is "right"—it only reflects the players' beliefs.

[4] According to put-call parity property for an at-the-money European option, the value of both call and put options is equal as long as the spot price of the underlying asset equals the strike price.

# 4. Option Pricing Formulas

Several option pricing formulas are described in the literature (see, e.g., Haug 2007; Rouah and Vainberg 2007). The first known and the simplest formula is the Bachelier formula for at-the-money options (Haug 2007, 13):

$$c = p = \sigma\sqrt{\frac{T}{2\pi}} \approx 0.4\sigma\sqrt{T}$$

, (1)

where *c* denotes the price of an at-the-money call option; *p* stands for the price of an at-the-money put option; $\sigma$ denotes the standard deviation of the price of the underlying security during a one-time period. *T* is time to maturity (until expiration). Formula (1) could be used as an approximation for the more advanced Black-Scholes-Merton (BSM) model for option pricing, but there are some discrepancies for a high volatility and for a longer period to maturity of the option. The Polya approximation (see Pianca 2005) provides a close tracking of the BSM at-the-money price. The Polya approximation formula is:

$$c = S\sqrt{1 - e^{-v^2 t/(2\pi)}}$$

, (2)

where *S* denotes a spot price of the underlying asset and *v* denotes the price volatility defined as the standard deviation of the price divided by the price:

$$v = \sigma / S. \quad (3)$$

If $v^2 t/2\pi \ll 1$, then $\sqrt{1 - e^{-v^2 t/(2\pi)}} \sim \sqrt{v^2 t/2\pi}$, from which the relation to the Bachelier formula is evident.

Volatility is dimensionless but is often expressed as a percent. Thus, if $\sigma = S/3$, then v = 33 percent. In the literature, there are several more sophisticated option pricing formulas that consider skewness and kurtosis of price distribution, account for stochastic volatility, accommodate jump-diffusion processes, and so forth. For our analysis, Polya approximation or Bachelier pricing provide a sufficient precision, and offer a direct way to attribute a fraction of risk to the variance in weather prediction.

# 5. Attribution: Market Risk versus Accuracy of Weather Prediction

Consider a stylized model of corn prices with two major sources of uncertainty:

- weather in June–July that determines supply of corn and soybeans
- state of the global economy that determines demand and non-weather–related factors in general

A relation between weather and corn and soybean yields is well described in the literature (see, e.g., Westcott and Jewison 2013) and summarized in the Annex. Weather factors and the state of the global economy are effectively independent. Let $\sigma_c^2$ denote the variance of the corn price and $\sigma_s^2$ denote the variance of the soybean price, then:

$$\sigma_c^2 = \sigma_{Wc}^2 + \sigma_{Mc}^2 ; \qquad (4)$$

$$\sigma_s^2 = \sigma_{Ws}^2 + \sigma_{Ms}^2 ; \qquad (4.A)$$

where $\sigma_{Wc}^2$ and $\sigma_{Ws}^2$ denote the variance in price attributed to weather-related uncertainty for corn and soybeans, whereas $\sigma_{Mc}^2$ and $\sigma_{MS}^2$ denote the price variance attributed to market uncertainty and represent the market risk associated with holding one bushel of corn and one of soybeans, respectively. We are interested in the terms $\sigma_{Wc}^2$ and $\sigma_{Ws}^2$ for the next section (we continue with corn, since calculations for soybeans are similar):

$$\sigma_{Wc}^2 = \sigma_c^2 - \sigma_{Mc}^2:$$

$$\sigma_{wc} = \sqrt{\sigma_c^2 - \sigma_{Mc}^2} \qquad (5)$$

By definition, $\sigma_{wc}$, $\sigma_C$ and $\sigma_{Mc}$ are in dollars per bushel ($/BU).

Formulas (4) and (4A) imply that the prices of corn and soybeans have Pearson correlation close to 1. Data do show that this correlation is about 90 percent, suggesting that this model is indeed a good approximation (see Annex Figures A.2.A and B). Unlike the example in Section 3, this simple model gives no advantage for joint hedging of corn and soybean positions.

As in the example in Section 2, we use DIA as a proxy for the market risk. To calculate $\sigma_{MC}$ (the market risk associated with holding one bushel of corn), we first should calculate how many shares of DIA could be bought for the same amount as one bushel of corn. The ratio *k* is the price of corn $(P_C)$ divided by the price of DIA $(P_D)$:[5]

$$k_c = \frac{P_C[\frac{\$}{BU}]}{P_D[\frac{\$}{Share}]}.$$

Let $\sigma_{DIA}$ denote standard deviation of DIA, then:

$$\sigma_{Mc}\frac{\$}{BU} = k_c\frac{Share}{BU}\ \sigma_{DIA}\frac{\$}{Share}.$$

Applying market data, we can estimate the standard deviation of corn prices and standard deviation of DIA. For the numerical analysis, we use an ETF—"CORN"—that replicates the corn futures market[6] and DIA (another ETF) that represents market factors not specifically related to corn. DIA tracks the Dow Jones Index and is widely used to characterize stock market dynamics. Based on historical data on daily CORN and DIA pricing (from 2010 to the end of September 2018[7]), we calculated daily volatility of CORN and DIA as well as annualized volatility.[8] Then, from Formula (3) we estimate standard deviation ($\sigma = v * S$).

[5] In other words, one can be long one bushel of corn and be exposed to the volatility of corn price or, alternatively, sell a bushel of corn (short of corn) to buy DIA and be exposed to market volatility. The difference in risk could be attributed to weather prediction (holding corn is riskier than holding DIA).

[6] The "Teucrium Corn Fund (NYSE: CORN) provides investors **unleveraged** direct exposure to corn without the need for a futures account. CORN provides **transparency** to investors by investing in a **known benchmark** (described below), **listing all holdings** nightly, and providing **future roll dates**. CORN was designed to reduce the effects of rolling contracts (and **contango and backwardation**) by not investing in front-month (spot) futures contracts and thus limiting the number of contract rolls each year". See: **http://teucriumcornfund.com/**.

[7] For volatility calculation, we consider longer time than for average annual price. To be on the conservative side for calculation of VOI, we excluded a period of elevated prices from calculation of an average weighted price. For example, in 2012–2013, an average price was about $6.5/BU.

[8] For a detailed explanation of volatility calculation see: **https://www.fool.com/knowledge-center/how-to-calculate-annualized-volatility.aspx**

Annualized corn volatility is 23 percent and DIA volatility is 14 percent. The price of corn is about $3.8/BU and DIA is about $260 per share. Then:

$$k_c = \frac{3.8(\frac{\$}{BU})}{260(\frac{\$}{Share})} \approx 0.0146 \qquad \text{and}$$

$$\sigma_{wc} = \sqrt{\sigma_c^2 - \sigma_{Mc}^2} = \sqrt{\sigma_c^2 - (k_c \sigma_{DIA})^2}\ , \tag{6}$$

so that

$$\sigma_{wc} = \sqrt{(0.23 * 3.8)^2 - (0.0146 * 0.14 * 260)^2} \approx 0.69[\frac{\$}{BU}] \tag{7}$$

$$\sigma_{Mc} = 0.0146[\frac{Share}{BU}\} * 0.14 * 260[\frac{\$}{Share}] \approx 0.53[\frac{\$}{BU}]. \tag{8}$$

Thus, the standard deviation of the corn price (Formula 3) is 0.23 × 3.8 = 0.87[$/BU]; from (7), the share of weather-related uncertainty is about 0.69[$/BU]; and share of market-related uncertainty is about $0.53[\frac{\$}{BU}]$ (Formula 8).

We apply the same methodology for soybeans, calculating volatility using data on the Teucrium Soybean Fund (NYSE: SOYB) that, like CORN, provides direct exposure to soybeans futures without the need for a futures account.

Annualized volatility for soybeans is 21 percent; the price of soy was about $9.9/BU[9] and DIA $260 per share—then $k_s = 0.038$, so that

$$\sigma_{ws} = \sqrt{(0.21 * 9.9)^2 - (0.038 * 0.14 * 260)^2} \approx 1.55[\frac{\$}{BU}] \tag{9}$$

$$\sigma_{Ms} = 0.038[\frac{Share}{BU}\} * 0.14 * 260[\frac{\$}{Share}] \approx 1.39[\frac{\$}{BU}]\ . \tag{10}$$

The standard deviation of the price of soybeans (Formula 3) is about 2.08 [$/BU]; the share of weather-related uncertainty is about 1.55[$/BU]; and the share of market-related uncertainty is about $1.39[\frac{\$}{BU}]$. The squares of these quantities (i.e., the variances) add but the "shares" do not. Table 1 summarizes uncertainty attributed to weather and market calculated per bushel of corn and soybeans.

[9] Average spot price for the period 2014–2018.

**Table 1. Attribution of Price Uncertainty (standard deviation) to Weather and Market per bushel of Corn and Soybeans**

| | Price uncertainty $[\frac{\$}{BU}]$ | Weather-related uncertainty $[\frac{\$}{BU}]$ | Market-related uncertainty $[\frac{\$}{BU}]$ |
|---|---|---|---|
| Corn | 0.87 | 0.69 | 0.53 |
| Soybeans | 2.08 | 1.55 | 1.39 |

# 6. Calculating Value of Information

Annual corn production in the United States is about 15 billion bushels; for soybeans, about 4.2 billion bushels.[10] The daily average price of corn (weighted by daily trading volume) is $3.8/BU, calculated for the period from January 2014 to the end of August 2018; the daily average price for soybeans is $9.9/BU. The total annual volume of corn is worth about $53 billion per year; for soybeans, about $42 billion per year. As with any other commodity, corn and soybeans are primarily traded on the futures market. Several different futures contracts with different expiration dates are traded on the futures market simultaneously. Low predictability of commodity prices is an important factor of risk for commodity consumers and producers. Prices for corn and soybeans exhibit relatively high volatility (see Annex). Price fluctuations depend both on the weather (which determines corn supply at the time of harvesting) and on the state of the economy (which determines demand).

Using approximations of the BSM[11] option pricing model for an at-the-money call option (Bachelier's option pricing, Formula 1, is a good approximation of the price for an at-the-money call option), an annualized value of risk associated with price uncertainty (standard deviation) per one bushel of corn is $0.4 * \sigma_C$ and per one bushel of soybeans is $0.4 * \sigma_S$ (in this calculation we use an annual volatility, therefore T=1[12]).

Using historical data, an annualized value of risk associated with the price uncertainty is $1/\sqrt{2\pi} \times$ implied volatility $\times$ price = 0.4*0.87[$/BU] = $0.35 [$/BU] for corn; and 0.4*2.08 [$/BU] =$0.83 [$/BU] for soybeans. The total annual risk for the corn market due to price volatility is therefore about $5.25 billion (= 0.35 [$/BU]*15 [BBU]) and about $3.5 billion in case of soybeans. In other words, the uncertainty (standard deviation) in the price of corn costs society about $5.25 billion per year; uncertainty in the price of soybeans costs about $3.5 billion per year.

[10] Calculated for the period from 2014–2018.
[11] See: https://www.investopedia.com/university/options-pricing/black-scholes-model.asp
[12] The fraction of corn price variance attributed to weather predictions changes during the year. It is highest in spring and lowest in late fall. It may be advisable to consider seasonal fluctuation of weather-related risk. It will require calculating an option value for shorter than a one-year period.

## Table 2. Total Value of Risk Associated with Price Uncertainty (standard deviation) and Its Attribution to Weather and Market

| | Price uncertainty $[\$\boldsymbol{B}]$ | Weather-related uncertainty $[\$\boldsymbol{B}]$ | Market-related uncertainty $[\$\boldsymbol{B}]$ |
|---|---|---|---|
| **Corn** | 5.25 | 4.20 | 3.18 |
| **Soybeans** | 3.5 | 2.69 | 2.34 |

Assume that the weather-related standard deviation were reduced by 30 percent—then the new value of $\sigma_{wc}$, using Formula (7), is 0.7*0.69$/BU = 0.49 $/BU. This reduction in the weather-related standard deviation will result in a reduction in the standard deviation for corn prices:

$$\sqrt{(0.49)^2 + (0.0146 * 0.14 * 260)^2} = 0.72 \left[\frac{\$}{BU}\right].$$

The reduction in the standard deviation attributed to an improved weather forecast is

$$0.87 \left[\frac{\$}{BU}\right] - 0.72 \left[\frac{\$}{BU}\right] = 0.15 \left[\frac{\$}{BU}\right].$$

We apply the Bachelier formula (1) for an at-the-money call option to calculate the benefits of an improved weather forecast per bushel of corn:

0.4*$0.15/BU = $0.06/BU.

With annual US corn production of about 15 billion bushels, the total value of information leading to a 30 percent reduction in weather uncertainty is about $0.9B (0.06[$/BU]*15[BBU]=$0.9 billion).

For soybeans, the new value of $\sigma_{ws}$ is 1.76[$/BU]. Reduction in the standard deviation of the market price of soybeans attributed to improved weather forecasting is about 0.32[$/BU] (2.08[$/BU]-1.76[$/BU]= 0.32[$/BU]).

Applying the Bachelier formula (1) for an at-the-money call option to calculate VOI for soybeans: 0.4*$0.32/BU = $0.128/BU. Annual production of soybeans in the United States is about 4.2 billion bushels—thus, the total value of information is about $0.54B

(0.128[$/BU]*4.2[BBU]=$0.54 billion). Therefore, the total annual benefit of risk reduction (both for corn and soybeans) is $1.44 billion.

Calculations of VOI for corn and soybeans are summarized in Table 3.

## Table 3. Summary of VOI Calculation

| | Price volatility [%] | SD of price $/BU | SD of market [$/BU] | SD of weather [$/BU] | Reduction weather SD [%] | SD of weather after reduction [$/BU] | SD of price after weather reduction [$/BU] | Market value of risk before reduction (Bachelier) [$Billion] | Market value of risk after reduction (Bachelier) [$Billion] | VOI of reduction [$Billion] |
|---|---|---|---|---|---|---|---|---|---|---|
| **Corn** | 0.23 | 0.87 | 0.53 | 0.69 | 30 | 0.49 | 0.72 | 5.25 | 4.32 | 0.9 |
| **Soybeans** | 0.21 | 2.08 | 1.39 | 1.55 | 30 | 1.08 | 1.76 | 3.49 | 2.96 | 0.54 |

*Note:* SD stands for standard deviation.

The total VOI for corn and for soybeans attributed to a 30 percent reduction in the standard deviation of weather production is about $1.44 billion per year.

If the weather uncertainty is totally eliminated, then residual volatility equals 0.14—and the total annual risk for the corn market due to price volatility is therefore about $3.19 billion. The theoretical maximum VOI (value of perfect weather information) equals the difference between an actual and residual value of risk for corn:

$$(0.23 - 0.14) * 3.8\left[\frac{\$}{BU}\right] * 0.4 * 15[BBU] = 0.137\left[\frac{\$}{BU}\right] * 15[BBU] = \$2.05B.$$

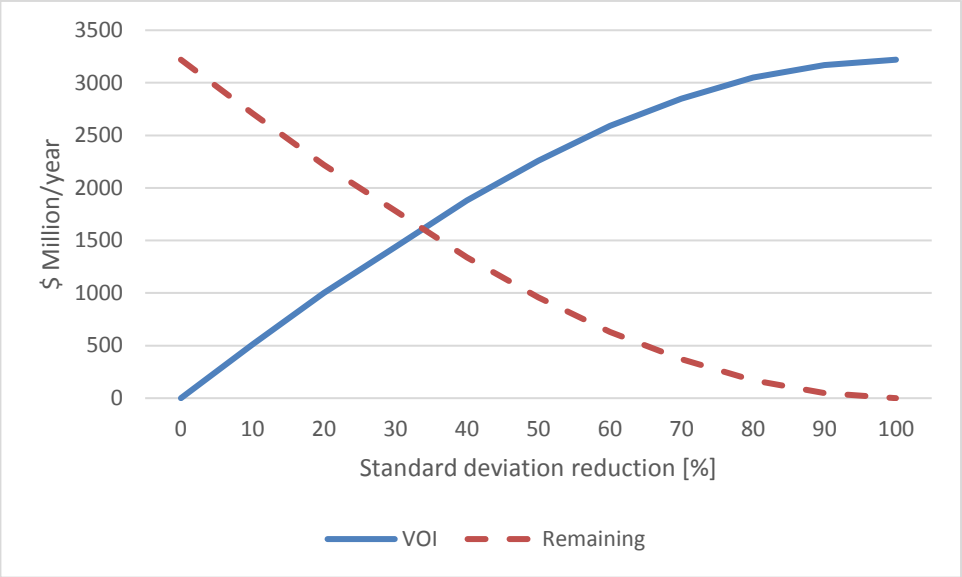
For soybeans, the theoretical maximum VOI is $1.16B per year.

The annual value of improved weather forecasting for the United States is about $1.44 billion per year. The total present VOI calculated with a 3 percent discount rate is about $22 billion, assuming the Earth-observing system is in operation for 20 years.

This accounts for about 36 percent of global corn production and about 34 percent of soybean production. Thus, the global value of the improvements in weather forecasting could be up to $63 billion.

Figure 1 illustrates the benefits of standard deviation reduction (for corn and soybeans) and the additional value of learning (weather prediction). The reduction of standard deviation (in percentage terms) is on the horizontal axis; the corresponding benefits (blue line) and remaining value of risk (gray line) are on the vertical axis.

## Figure 1. Benefits of Risk Reduction for Corn and Soybeans




Source: Authors calculations.
Note: The solid line depicts risk reduction in millions of dollars as a function of reduced standard deviation in weather predictions, calculated in percentage terms; the dashed line is remaining risk attributed to remaining uncertainty in the accuracy of weather predictions.

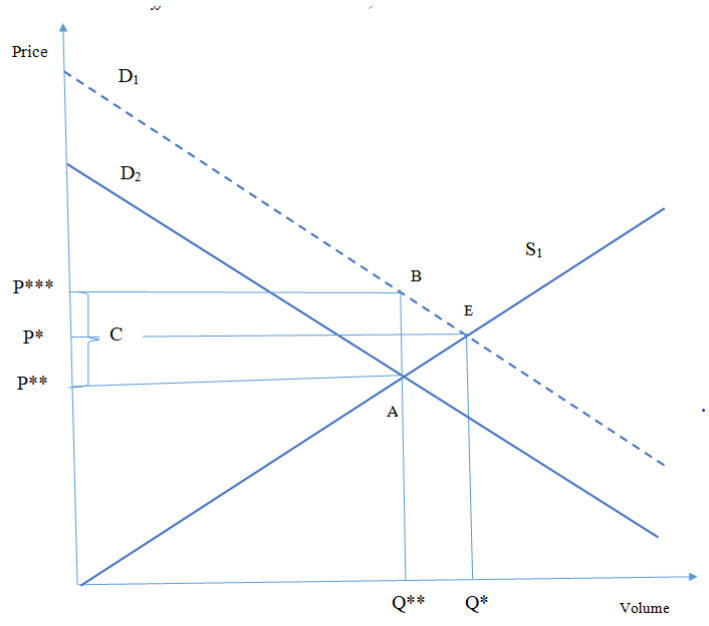
The VOI is a concave function of the standard deviation reduction. The value of perfect weather information would be around $3.3 billion per year. A complete elimination of weather-related variance in price forecasts for corn and soybeans is impossible—but even a 30 percent reduction in the standard deviation yields slightly less than half of the theoretical maximum.

# 7. VOI in Welfare Indicators

Section 6 examined the VOI in a partial equilibrium context presenting a gross VOI. In this section, we put the valuation problem in a general equilibrium framework. In a general equilibrium model, somebody's expenses could be somebody else's revenue. General equilibrium models allow quantifying the net losses for society attributed to price volatility. Low predictability of commodity prices is an important risk factor for commodity consumers and producers. Prices for corn and soybeans exhibit relatively high volatility (see Figure A.2A and A.2B). Fluctuations of these prices depend on both the weather that determines the supply of corn and soybeans by the time of harvesting and the state of the economy that determines demand. Uncertainty influences the business decisions of both consumers and producers of grain. Most market participants actively hedge commodity prices using futures (and/or options) contracts. Application of an optimal hedging strategy using futures allows market participants to "lock in" a price level. Higher predictability of price means lower cost of hedging. Application of a hedging strategy creates assurance regarding price but costs money for the market agents that are coping with risk.

The cost of hedging should be treated as a part of the cost of producing and consuming corn and soybeans. In the presence of these costs, the economy may reach a relatively low equilibrium and will experience a corresponding welfare loss. We illustrate this in Figure 2.

### Figure 2. Price Uncertainty and Net Welfare Loss



In Figure 2, $D_1$ denotes demand in the absence of uncertainty and $D_2$ is a risk-adjusted demand curve, both as functions of supply, Q. For the sake of argument, we assume that consumer is always hedging the grain price. The cost of hedging equals C. Here we assume that the grain buyer makes the best possible prediction of the future price, given all available information about soil moisture, weather forecasts, and so on. In order to guarantee this price, the grain buyer also purchases a call option with strike price equal to P** and an up-front premium of C. By paying this premium, the consumer guarantees a price less than or equal to P**.

Note: $D_1$ is demand function in a risk-free case. $S_1$ is supply function. $D_2$ is a "modified" demand function that reflects hedging cost equal to C, which is the difference between P*** and P**.

As a result, the demand curve shifts downward. A new demand curve is $D_2$. The equilibrium price drops from P* to P**. Grain producers are also exposed to price uncertainty. In order to guarantee both price and required volume, they also bear some additional cost. An initial supply curve $S_1$ should shift upward; however, the introduction of hedging instruments like futures and options allows the buyer and seller to split hedging costs. For graphical illustration we assume that the buyer always pays the seller an upfront premium, $C(\sigma)$, to guarantee the future price, and this premium is sufficient to cover the seller's cost of uncertainties. The supply curve, $S_1$, doesn't shift upward, but the suppler receives actual compensation for one bushel of grain less than or equal to P*** = P**+ C. If an actual spot price falls below P**, the buyer does not exercise the call option and buys grain on the spot market for a price below P**, letting the call option expire.

In the presence of uncertainty, society reaches a relatively lower equilibrium and therefore experiences welfare losses. The new equilibrium grain production shifts from Q* to Q** and society experiences the net losses equal to the area of triangle ABE. Welfare loses are equal to $C \times (Q^* - Q^{**})/2$. The area of ABE is determined by slopes of $D_2$ and $S_1$ and by $C(\sigma)$. Let the absolute slope of the demand function be *d* and the slope of the supply function be *s*. Then the area of ABE equals $(C^2/(d+s))/2$. Recall C denotes cost of hedging. The cost of hedging equals the value of the at-the-money call option. From (1) $C= 0.4^* \sigma$ (where $\sigma$ denotes the standard deviation of the grain price). The welfare loses are $0.08\, \sigma^2/(d+s)$. Reduction of the standard deviation by $\alpha$ ($0<\alpha<1$) results in welfare loses of $0.08\, \sigma^2/(d+s)(2\alpha - \alpha^2)$. The hedging cost C has a negative effect on demand, similar to the impact of a tax on consumption. Like hedging costs, taxes on consumption shift the demand curve downward and result in net welfare losses equal to the area of triangle ABE. In the economics literature, the net welfare losses are known as a "deadweight losses".

# 8. Conclusions

Options theory provides tools for monetizing reductions in uncertainty with regard to risks that are traded on options markets. Buyers and sellers agree on a price for hedging risky positions. Familiar options pricing models translate this price into a standard deviation for the underlying risky quantity. Reductions in uncertainty of this quantity, combined with market information on the price and volume of the market, can then be monetized as consumer surplus in a partial equilibrium model, or as higher equilibrium value in a more general setting.

The application of these techniques is illustrated in a stylized example involving NASA's SMAP mission for reducing uncertainty in soil moisture. By decomposing the price variance for soybeans and corn into a market and a weather component, it is possible to quantify the effect of uncertainty reduction in the weather component on the price of corn and soybeans futures. A 30 percent reduction in the weather component leads to a yearly US consumer surplus of $1.44 billion. As this uncertainty is reduced, the value of additional reductions shrinks. Nearly half of the value of perfect weather information is obtained by reducing the weather uncertainty by 30 percent.

A complete VOI study requires several additional aspects not covered here—additional impacts of uncertainty reduction on other crops, flood prediction, insurance prices, global markets, and so on—should be factored in, as well as mission costs. Further, the SMAP contributions must be compared to other measurement programs targeting soil moisture prediction. Finally, the actual uncertainty reduction achieved by SMAP relative to existing prediction methods must be established. The goal of the present study is to show how such information could be used in combination with market tools to monetize uncertainty reductions.

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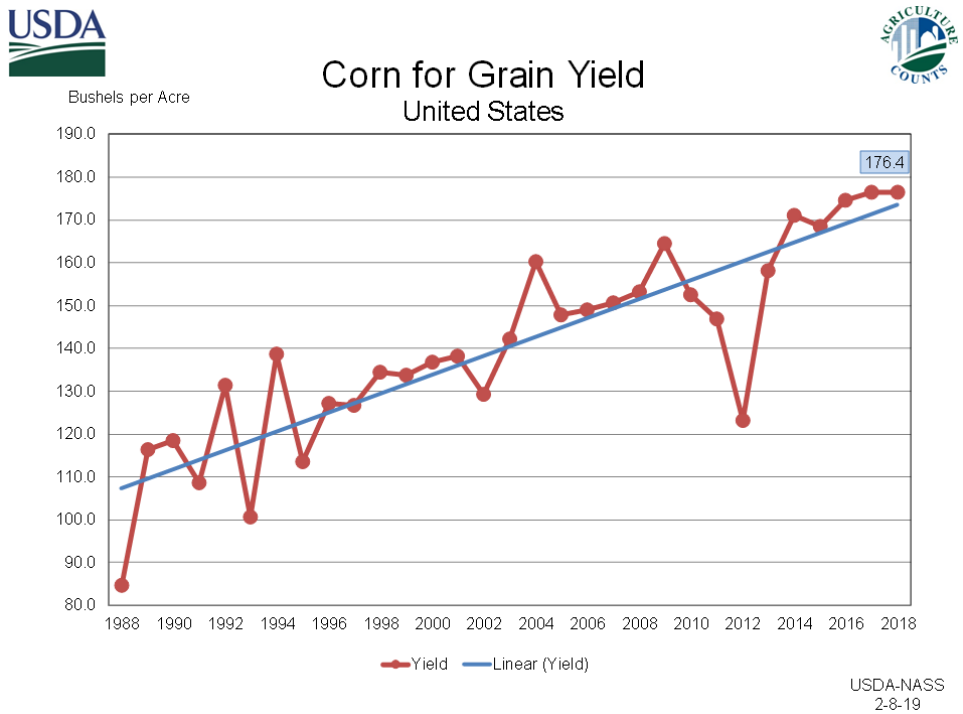
# Annex. Variability of Crop Production and Price Volatility

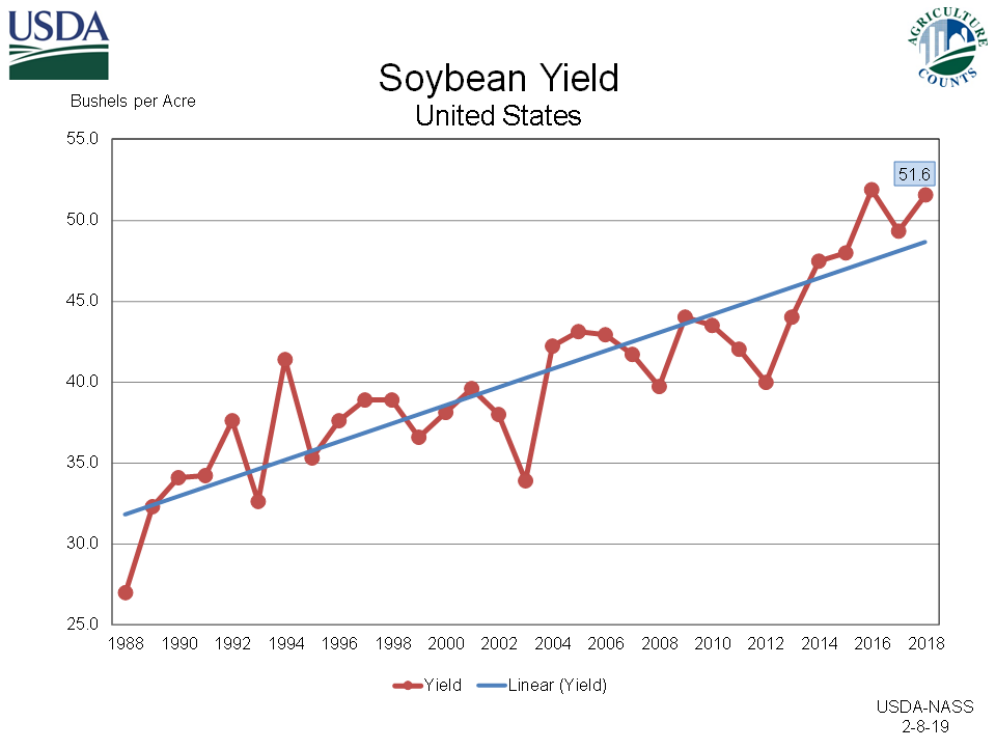
The analysis of historical soybean and corn yields suggests a notable variability (see Figure A1, A and B).

### Figure A1.A. Corn Yield Variability and Long-Term Trend (bushels per acre)




Source: **https://www.nass.usda.gov/Charts_and_Maps/Field_Crops/cornyld.php**

**Figure A1.B. Soybean Yield Variability and Long-Term trend (bushels per acre)**




Source: **https://www.nass.usda.gov/Charts_and_Maps/Field_Crops/soyyld.php**

Westcott and Jewison (2013) provide detailed analysis of the weather effect on corn and soybean productivity and established the relationship between weather and crops yields.[13] Variation in the productivity of corn and soybeans leads to variations in the supply of these crops with corresponding variations in corn and soybean prices. While deviation of corn and soybean production from trend is about 7 percent[14] of an expected value, the price volatility is above 20 percent.

Deviations from trend is the reason for supply shocks. A limitation in predictability of an actual supply is the foundation for price volatility (see Figure A2, A and B).

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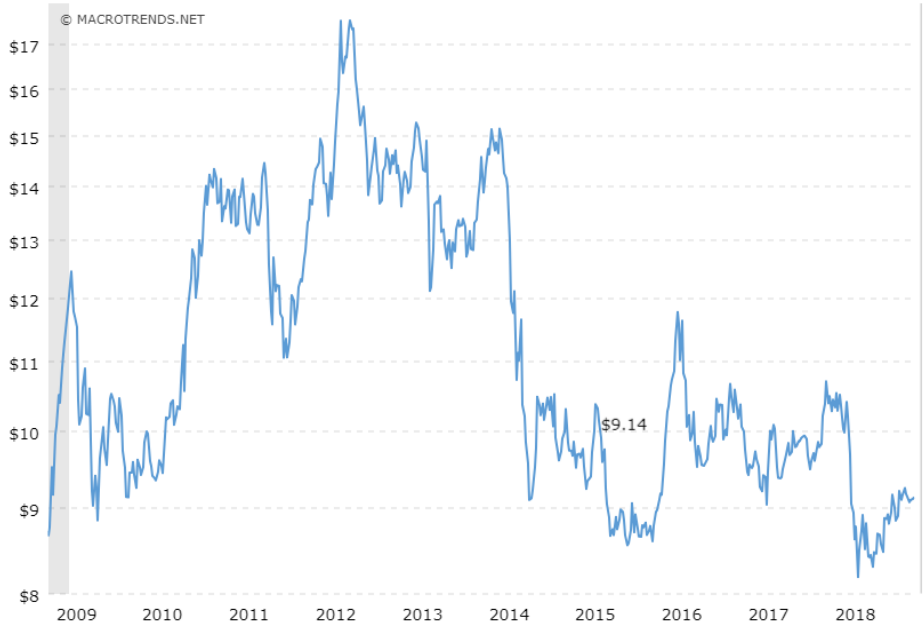
[13]Paul C. Westcott, USDA, Economic Research Service Michael Jewison, USDA, World Agricultural Outlook Board "Weather Effects on Expected Corn and Soybean Yields" (**https://www.usda.gov/oce/forum/past_speeches/2013_Speeches/Westcott_Jewison.pdf**)
[14] Calculated using USDA data on historical corn and soybean production (**https://www.nass.usda.gov/Statistics_by_Subject/index.php?sector=CROPS**)

## Figure A2.A. Historical Corn Prices of Corn ($ per bushel)


Source: **https://www.nass.usda.gov/Charts_and_Maps/Field_Crops/cornyld.php**

## Figure A2.B: Historical Soybean Prices ($ per bushel)




Source: **https://www.nass.usda.gov/Charts_and_Maps/Field_Crops/soyyld.php**

Based on an extensive econometric analysis, Westcott and Jewison (2013) concluded that “weather during the growing season is critical for corn and soybean yield development.” Improved weather predictions should improve predictions of corn and soybean production, closing gap between an actual and predicted production and therefore reducing price volatility.