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Valuing New Random GM Traits: The Case of Drought Tolerant Wheat

Sumadhur Shakya
William W. Wilson
Bruce Dahl

Department of Agribusiness and Applied Economics
Agricultural Experiment Station
North Dakota State University
Fargo, North Dakota 58108

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Abstract

There has been an increase in support for developing genetic modification (GM) technology in wheat. The purpose of this paper was to develop an analytical model to analyze the value of GM traits at different phases of development. To do so we developed a stochastic binomial model of real options. The results indicate that the value of drought tolerant wheat using GM technology is in-the-money at each phase of development. The greatest value would accrue to the Prairie Gateway and northern Great Plains regions in the United States.

Valuing New Random GM Traits: The Case of Drought Tolerant Wheat

Introduction

Development of genetically modified (GM) crops is continuing on numerous fronts and in several countries. Wheat is one of the next crops to be commercialized with genetically modified ingredients. It will be one of the first food grains in which GM traits are introduced, and will likely be a precursor to similar developments in other food grains. Some traits have been targeted for many years in extensive breeding programs but, now some of these traits are targeted using GM technology and marker-assisted-selection (MAS) which are thought to be prospectively lower cost and more effective than conventional crop improvement technologies. These are still costly technologies and research and development using these techniques are subject to numerous risks.

GM wheat is currently being developed in a number of countries and by a number of companies. Traits under development in wheat using GM techniques include Fusarium resistance (Huso & Wilson, 2005; Tollefson, 2011a; Valliyodan & Nguyen, 2006), drought resistance in Australia, and protein quality. Since the late 2000s all of the major agbiotechnology companies have made announcements indicating their intentions to enter the GM wheat market and in 2011 there were field trials by a number of companies in the United States and Australia. Amongst these, the most common traits being pursued include yield, drought tolerance (DT) and nitrogen use efficiency. Of interest to this study is that drought tolerance is extremely random, and the value of the trait results from numerous random events.

Trait development strategy is fraught with randomness and extended periods for development, which results in substantial risks. It is generally thought that developing a trait can take at least 10 years. The trait pipeline typically is referred to as comprising phases ranging from proof of concept to regulatory approval. Each of these steps takes several years, is costly, and the outcome is uncertain. The costs of trait development range upwards from $130 million, and Monsanto indicated its current effort in wheat will cost at least $150 million. Finally, revenue streams from trait development do not ensue until a period following regulatory approval. For these reasons, trait development is highly risky and strategic, and as a result, real options are an appropriate methodology for valuing traits during the trait development period.

The purpose of this paper is to develop a stochastic model using real options to value drought tolerant wheat. The model builds on previous studies using real options to value investments in research and development (R&D) (Brach & Paxson, 2001; Jensen & Warren, 2001; Luehrman, 1997; Morris, Teisberg, & Kolbe, 1991; Seppä & Laamanen, 2001) and on the use of real options to value GM traits in crops (Carter, Berwald, & Loyns, 2005; Flagg, 2008; Furtan, Gray, & Holzman, 2003; Wilson, 2008). Its major contribution is that it captures the effects of numerous *ex ante* random variables impacting trait development, resulting in random outputs in a real option framework and interpreted in the context of firm-level decision-making. Stochastic simulation is used to account for randomness in variables representing uncertain outcomes associated with development of GM trait(s) including uncertainty and cost associated with their commercial release.

Background

Wheat is one of the largest acre food crops, but has not been a recipient of the new technologies that have benefited corn, soybeans, canola and cotton. Compared to these crops, wheat has been losing its competitiveness for a number of reasons.[1] Area planted to wheat in the United States has declined by 30-40% since the mid-1980s. During the same period, canola acreage in Canada has increased to now exceeding wheat acres, and there have been important geographical shifts in the composition of crops planted in these countries. Generally, this has been for lesser wheat acres and a gradual shift northerly and westerly to dryer areas.

Since 1996 a number of GM traits have been introduced in competing crops. For corn, Round-up Ready (RR), *Bacillus thuringiensis* (BT) and several other traits have been developed and widely adopted. Some of these are now stacked in multiples of three or four traits in a single variety. During 2011 there was attention to the emerging new traits and technologies in corn (Birger, 2011; McMahon, 2011; "Search for Super Corn Seeks to Limit Nitrogen Use, Pollution," 2011) and challenges and opportunities for commercialization. Looking forward, a large number of traits are under development and expected to be commercialized in the next 10 or more years (Wilson & Dahl, 2010a, 2010b). For corn, there are at least 21 new GM traits under development. Some are producer traits, some consumer and some processor traits. Some of these traits are developed individually and some through joint initiatives. A comparable number and composition of traits is under development for soybeans. One of the most important traits for corn is drought-tolerance (DT) and after being under development for many years, it was deregulated in late 2011, and farm trials are planned for 2012 in North America.

Development of GM wheat is important for a number of reasons (see (Wilson, 2004; Wilson, Janzen, Dahl, & Wachenheim, 2003) for a comprehensive discussion of the issues related to GM wheat). First, wheat will be one of the first food grains in which GM traits are introduced, and will likely be a precursor to similar developments in other food grains. Second, wheat is traded among many importing and exporting countries, and many of these have very different mechanisms for regulating trade in GM crops and for marketing products with GM ingredients. Third, there is no doubt demand will become highly differentiated for products produced with/without GM ingredients, and/or requirements to provide information to consumers, among these countries.

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[1] There have been numerous presentations to explain the extent of these changes. See in particular, Wilson (2008).

Several technologies exist for improving wheat including conventional breeding[2], marker-assisted-selection (MAS) and genetic engineering (GM), amongst others. The focus of this article is on drought tolerance in wheat (discussed below). Drought tolerance has been a breeding goal for many years and has been described in the scientific literature for at least 40 years. Drought tolerance is felt to be difficult using conventional techniques due to the complexity of the plant's metabolic pathways to the plant. The appeal of using GM techniques for drought tolerance is that it may be more efficient in improving the crop.

Integration of these breeding technologies (conventional, MAS and GM) has brought about a paradigm shift in crop development referred to "Seeds and traits" as a business function. It involves combining novel genetic traits with elite germplasm to develop crops that thrive while expressing the desired trait. The steps include discovering novel genes, transferring them into the cells of plants, optimizing the expression of the genetic trait in plants in the correct plant tissues, at the appropriate time and in sufficient levels and incorporating, through breeding, the genetic trait into commercially viable varieties or hybrids. As a business strategy, introduction of genetic traits via biotechnology does not reduce the importance of superior germplasm in the host plant, nor does it replace the need for plant science and plant breeding (Dow AgroSciences, n.d.; Kaehler, 2006).

Round-up Ready had earlier been developed by Monsanto as a GM trait for wheat, but was withdrawn in 2004 in part due to anticipated consumer resistance. It was ultimately deregulated in the United States but not commercialized. Concurrently, Syngenta was developing a fusarium resistant trait, but never pursued commercialization. Following a number of years in which wheat acres declined in North America, largely being shifted to corn, soybeans, canola and cotton, a number of events unfolded which helped spawn the recent interest in GM wheat. One was a tri-lateral agreement amongst grower groups supporting development of GM wheat. The other was the radical escalation in prices during 2008 which precipitated concerns by end-users about the longer-term supplies and competitiveness of wheat.

Monsanto was the first to announce their intent to expand into GM wheat. This was followed within months by announcements from each of BASF, Bayer Crops Sciences, Limagrain and DOW. Each of these companies are following work that has already been initiated in Australia by the Victoria Agrobiosciences Center (VABC) and CSIRO. Indeed much of the initial and early work was done in Australia in which their

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[2] As example, a salt-tolerant gene has recently been introduced into durum wheat using non-genetically modified genes by CSIRO and the University of Adelaide.

primary initial focus was on drought.[3] These are in addition to near-simultaneous development of initiatives on GM wheat in China (Xia, Ma, He, & Jones, 2012). These firms and organizations have been pursuing varying strategies regarding acquiring germplasm, creating public-private partnerships, etc. In addition, to varying degrees they have each made claims about the traits they intend to develop using genetic modification. Most common, these include yield, drought tolerance and nitrogen-use-efficiency, amongst others. The criteria for selecting these traits are not exactly clear. Most likely, these choices are a result of experiences with other crops, plant stress, and anticipated changing geography of production, in addition to concerns of future water availability and cost (James, 2011; Rice Today, 2012; Sindrich, 2012).

Drought tolerance (DT) is an example of a stress trait. It has been described in numerous articles and is the focus of extensive media promotion (The Economist, 2011a, 2011b; Tollefson, 2011b; Wall Street Journal, n.d.). DT is also the focus for trait development in other crops including rice (Reyes, 2009). Genes are being identified to be activated by drought (i.e., the efficiency gain by drought resistant gene is realized when drought occurs) so as to avoid any yield penalty in normal conditions and indicated that “Drought tolerant crops look to be one of the most promising upcoming biotech traits in pipeline, providing ability to produce ‘more crop per drop’ of water” (Fatka, 2008). It is designed to provide farmers yield stability during periods when water supply is scarce by mitigating the effects of drought – or water stress – within a plant.

Drought tolerance has been analyzed fairly extensively in the case of corn (see Edmeades, 2006 for a detailed summary as of that time). Early results indicated that drought tolerant GM corn could potentially improve yields by 8-22% (15% average) under drought stress that reduces yields by 50 percent. This is commonly referred to as ‘trait-efficiency’ which is a critically important parameter in analyzing values and inter-firm trait competition. However, their comparisons do not distinguish trait efficiency between GM technology and that from market assisted breeding. Monsanto (Monsanto, 2008, 2009, 2010) indicated yield improvements of 6-10% in water stressed environments and testing of first and second generation DT corn varieties ranges from 6.7 to 13.4% for first generation tests, 9-15% for second generation, 9-10% yield

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[3] The status and outlook in Australia is described in several places, including: Agrifood Awareness, GM Wheat-Fact not Fiction: A 7-10 year program of consultation and collaboration, available at http://www.afaa.com.au/GM_wheat_2010/AFAA_GMWheatBrochure_WEB.pdf; and the most recent application for GM wheat trials in Australia are described at: International Service for the Acquisition of Biotech Applications, 2012, “Australia's Gene Technology Regulator Oks Trial for GM Wheat and Barley, and, Pocket K No. 38 Biotech Wheat, which is available at http://www.isaaa.org/resources/publications/pocketk/38/default.asp.

Finally, it was described previously at, http://www.financialexpress.com/news/droughttolerant-gm-wheat-under-trial-down-under/329163/ http://www.newscientist.com/article/mg19826623.500-droughtresistant-wheat-beats-australian-heat.html.

advantages were reported in low drought seasons and 15% in a high drought. More recently, Monsanto's drought-tolerant trait in corn (MON 87460) was deregulated in the United States and it is planning field trials for DT corn in 2012. The company said 40 percent of crop losses in North America are due to sub-optimal moisture (Reuters, 2011).

In addition to GM technology drought tolerance for wheat, alternative approaches to improve wheat include conventional breeding, as well as marker-assisted selection to improve water efficiency. There have been fewer studies in the case of drought tolerant wheat, in part because the trait discovery is just commencing (in 2010/11). In the case of GM drought tolerance, there have been 4 years of field trials in Australia. Results from those studies indicate that GM lines had yield 20 percent higher than conventional wheat varieties under conditions of drought stress (prospectively greater).

A challenge in valuing GM traits is that development time is long, it is highly risky as a result of uncertainties of numerous variables which are random, and it is costly. Typically, trait development including regulatory review takes about 10+ years, costs about $100 million and consists of a number of distinct phases. Estimates of these costs are difficult since they ultimately are firm-level activities and information is not readily published. Goodman estimated that development of a GM trait costs $60 million and can take 15 years. Recent estimates for regulatory costs are in the $6 to $15 million range (Bradford, Alston, & Kalaitzandonakes, 2006; Just, Alston, & Zilberman, 2006). Finally, one of the more recent studies that estimated these costs (McDougall, 2011) indicated the average cost of GM trait development is $136 million, and takes 13 years, though there is substantial variability across firms and traits on these estimates. Monsanto has indicated it will spend at least $150 million on its wheat initiative, though this includes costs of germplasm and breeding, in addition to MAS and GM. These costs reflect what are commonly referred to as discovery, proof of concept, early and advanced product development, and the regulatory phase, though the labels for these functions vary across firms.

Valuing R&D in Crop Development Using Real Options

Drought tolerance is of interest for a number of reasons. Most important for this study is that the value of traits that target drought is a result of numerous random variables and hence, the value of the trait is random. For these reasons it is ideally suited to be quantified using real options methodologies. Traditional methods for analyzing investment decisions in technology include net present value calculations, amongst others. However, these have difficulty capturing two important aspects that are important in valuing GM traits. One is the randomness throughout the development phase in numerous variables. The other is that technology (R&D) has embedded options which provide trait developers choices throughout the development process. By ignoring options and their value, there is a tendency to under-value technology projects, potentially resulting in an under-investment in R&D (Hayes & Abernathy, 1980; Hayes & Garvin, 1982; Schwartz & Trigeorgis, 2004; Schwartz, Trigeorgis, & Mason, 2004).

A number of recent studies have used a real options framework. The foundations are summarized in (Schwartz & Trigeorgis, 2004) who describe the evolution of this method and its role in valuing R&D. Features of the problem that are important include that 1) uncertainties are resolved through time and 2) managers have options that can be exercised throughout the duration of the project. Investments in R&D provide the option to continue, wait or abandon. Investing in R&D is equivalent to buying a call option and can be valued as a real option because it involves future opportunities, uncertainty and options. Earlier work on this methodology includes (Luehrman, 1997; Morris et al., 1991 for descriptions as to why real options can be used to model R&D); and applications by (Brach & Paxson, 2001; Jensen & Warren, 2001; Seppä & Laamanen, 2001). Since the process of crop development is staged in discrete phases and are measurable risks, there are uncertain outcomes to each stage, the real options approach lends itself well to use of this framework for valuation of GM traits.

Investing in R&D buys the option to abandon, wait, or continue to the next phase of development, which buys the option to continue to the commercialization phase. The option value, derived at each phase, can be either in-the-money (ITM), or out-of-the-money (OTM). If expected cash flows at an early development phase are positive, it is ITM and the developer would likely proceed to the next phase. If the value of the option is OTM, the developer can either wait, or abandon the project. This paper models R&D as a compound call option using a stochastic binomial option specification. The 'continue' growth option represents the decision to continue to the next phase and make further investment to get to the next phase. So long as the option is ITM, management could choose to invest and continue.

Earlier studies have used real options to analyze the value of GM traits in wheat (Flagg, 2008; Carter et al., 2005; Furtan et al., 2003). The two earlier studies analyzed decisions from a public sector perspective and were modeled as post-development timing options which were irreversible and the values were derived using the Black-Scholes model. Our approach differs from these in several respects. While these studies modeled the public costs and benefits of releasing a GM trait, we model the decision process of a private firm during the R&D process. Second, while these studies model a timing decision once the product is developed, we model real options confronting management of biotechnology companies during the development process. Their primary concern was the risks in the post-product development phase (e.g., the commercialization phase). In contrast, we model making R&D decisions through time and across phases of development. Lastly, many of the parameters are random in our approach, and for this reason we derived the option value at each phase using stochastic simulation.

Modeling GM Drought Tolerant Wheat Using Real Options

Overview

There are three steps to our empirical analysis. First we determine the value of DT wheat at the farm level. Second, we use stochastic simulation and stochastic efficiency with respect to a function (SERF) to derive the risk premium for DT wheat, which is interpreted as the expected value of the trait to growers. Farm budgets are simulated to measure risk and returns and SERF is then used to determine certainty equivalents with and without the trait. These results are used to derive the risk premium of the trait compared to no trait. The risk premium is defined as the value of the certainty equivalent that is required for a grower to be indifferent between the variety with and without the trait and is then used as the basis for pricing the new trait. Third, we use stochastic simulation and these values to derive the real option value of the R&D expenditure at each phase of development.

Farm Budgets and Trait Efficiency

We use farm budgets for each of the USDA defined crop reporting regions (USDA-ERS, 2010). The analysis quantifies risk to growers with and without the trait. Measures of risk and return per acre were derived through simulation of budgets, for each region. Random variables include crop yields, prices, seed costs, and prices for chemicals and fertilizer, and the probability of drought. Historical data for current technology (CT) wheat yields, prices and costs were fitted to distributions by budget region using data from 1996-2010 (USDA-ERS, 2010).

Using current technology, returns to labor and management were defined as:

$$\pi_i = \left[(\hat{P}_i * \hat{Y}_i) - (\hat{S}_i + \hat{F}_i + \widehat{C}_i + OC_i + FC_i)\right] \qquad \text{......Eq. (1)}$$

Where π_i is the return to labor and management, P is price, Y is yield for Current Technology, S is seed cost, F is fertilizer cost, C is chemical cost, OC is other operating costs, and FC is fixed costs for region i and variables with ^ are random and drawn from fitted distributions.

Yields for DT wheat were estimated relative to current technology yields (without the trait), trait efficiency and a probability distribution of drought coverage within the region. To accommodate a rightward rotation in yield distributions for drought technologies, yields for drought tolerant varieties were modeled assuming

$$Y_{DT} = Y_{CT} + (MaxY_{CT} - Y_{CT}) * TE * DCe \qquad \text{......Eq. (2)}$$

Where *CT* refers to Current Technology, Y_{DT} is the yield for Drought Tolerant, $MaxYield_{CT}$ is maximum yield, Y_{CT} is a random draw for yield, *TE is* trait efficiency is the trait efficiency for the drought tolerant variety and *DC* is Drought Coverage and is a random variable indicating distribution of the proportion of area covered by drought for the region.

There are a large number of distributions used in this analysis (for each random variable and region, as well as drought by region) and are not shown here, but are available from the authors. Distributions for drought coverage were fitted from data from the National Drought Mitigation Center (2010). We assigned river basins to ERS Budget regions based on which basin was predominant within each budget region. Then data for the basin assigned to the region was fitted to derive distributions for drought coverage for the budget region. Correlations between yield and drought coverage levels were estimated by mapping the joint cumulative distributions for yields and drought coverage assuming yield losses are due solely to drought. This means the joint cumulative distributions of yields and drought coverage were defined at percentiles of the distribution from 5 to 95% such that high yields were associated with low drought coverage and low yields with high drought coverage. Then correlations were computed from these joint observations. While yield losses can occur due to other environmental differences, this implies that lower CT yields occur when droughts cover a wider area of the budget region and should represent an upper bound for the value of the drought tolerant trait.

Trait efficiency is defined as the increase in yields as a result of the GM technology being inserted into conventional germplasm. While many companies are working on DT wheat, there are only a couple public references indicating efficiency for this trait. In our base case we define trait efficiency using results from field trials in Australia (the only published reference to date on trait efficiency). Results from these studies indicate a trait-efficiency of .20 and apply this to the yield difference from maximum yields for the region. This value was from results of field trials in Australia and implies that DT wheat variety can recover 20% of the yield loss attributable to drought. This is a critical value. There is also a subtle difference between corn and wheat in the interpretation of the probabilities. For corn, it is interpreted as 12 percent of losses can be saved during drought years due to the GM trait, whereas the results for wheat are interpreted that yields would be at least 20 percent more than conventional varieties under stress conditions. It is also a critical value for competition amongst trait providers as they try to compete by increasing their trait efficiency versus their competitors. In the analysis, our base case assumes a trait efficiency of .20 and we conduct sensitivities at .25. Increases in trait efficiency have the impact of shifting the function rightwards, as illustrated in Figure 1.

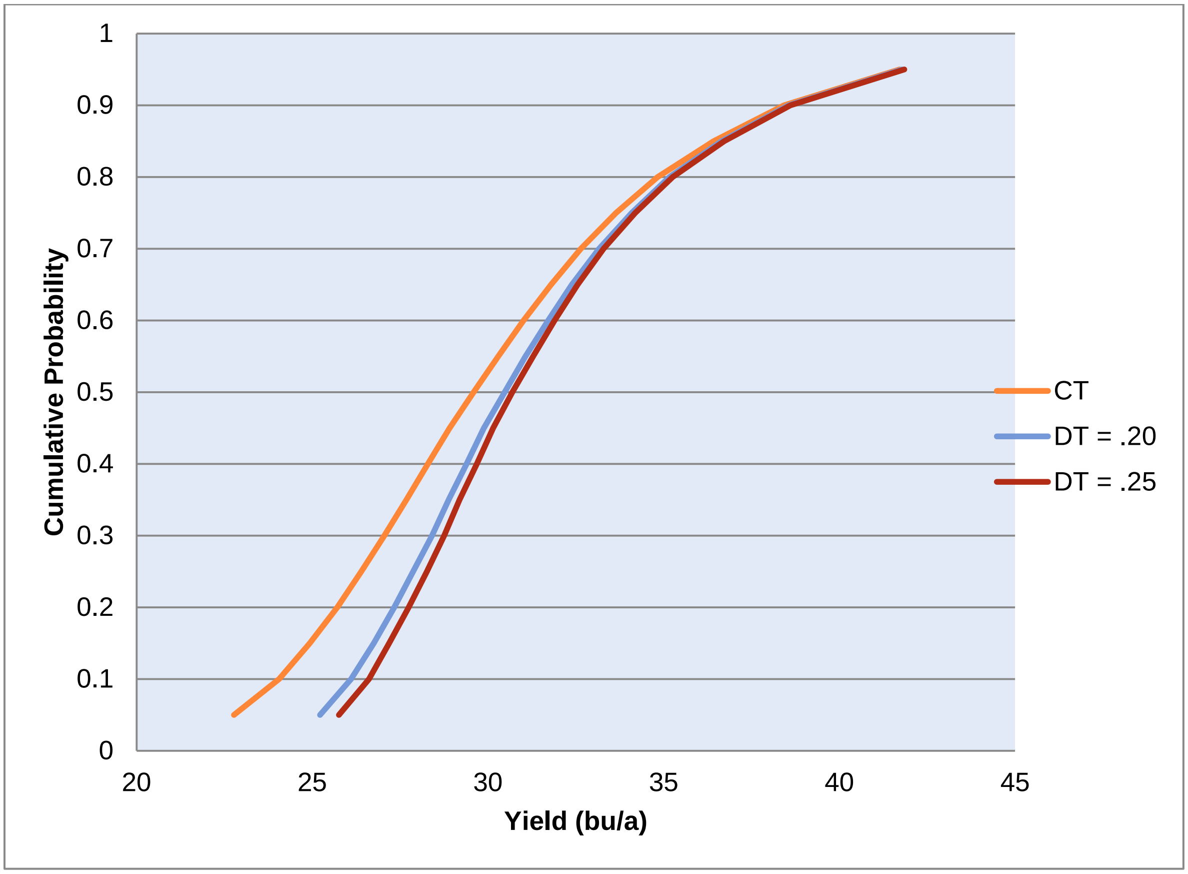


Figure 1 Comparison of Distribution of Wheat Yields for Conventional (CT), Drought Tolerant (DT) with Trait Efficiency of .2 and .25, Prairie Gateway Region.

Stochastic Simulation and Risk Premiums for Grower Trait Valuation

Monte-Carlo procedures using @risk (Palisade Corporation, 2007) were used to simulate the farm budgets with and without the DT trait. Random variables included yields, drought coverage, prices, and costs of seed, fertilizer and chemicals. In some cases, correlations among random variables were included. Budgets were iterated 10,000 times at which time stopping criteria indicated additional iterations would not improve the results.

SERF was used to derive the certainty equivalent that growers would place on a risky alternative relative to a no-risk investment (Hardaker & Lien 2003, Hardaker, Richardson, Lien, Schumann 2004). Certainty equivalents were estimated for wheat with and without the DT trait, by region for a range of Relative Risk Aversion Coefficients (RRACs) ranging from risk neutral (RRAC=0) to highly risk averse growers (RRAC=4). These were used to derive risk premiums by grower risk attitude for the trait, which are used as inputs in the option model.

Real Options Methodology

R&D in GM trait development is modeled as a compound option, consisting of the options to continue, wait or abandon. It is modeled as a binomial model using discrete event simulation which is one in which variables change at discrete points in time (in contrast to a continuous system is when state variables change continuously over time). The binomial model was specified as an option tree encompassing each of the phases of GM trait development, and simulated over a 15 year period. The model is an extension of (Jagle, 1999), which developed a real options model for "new product development" case. Different phases of the R&D and commercialization were defined along with estimates of the probability of success and costs for each phase (Seppä & Laamanen, 2001).

The model specifies a binomial option tree with multiple steps. These are illustrated in Figure 2. The preceding number before the developmental stage corresponds to option 1 to continue, 2 for the option to wait and 3 for option for abandon. Thus a sequential depiction of such numbers before a developmental stage illustrates the options at each phase of trait development which is contingent on previous states. At the end of each stage, there is an option to continue wait and abandon.

The option price is solved at the initial node of the tree, which is done by repeatedly applying the principles established above (Hull, 2004). The length of time is replaced with Δt years to account for the multiple steps in the binomial pricing method.

$$\Pi = e^{-r\Delta t}[p\Pi_u + (1-p)\Pi_d] \qquad \text{......Eq. (3)}$$

$$p = \frac{e^{r\Delta t} - d}{u - d} \qquad \text{......Eq. (4)}$$

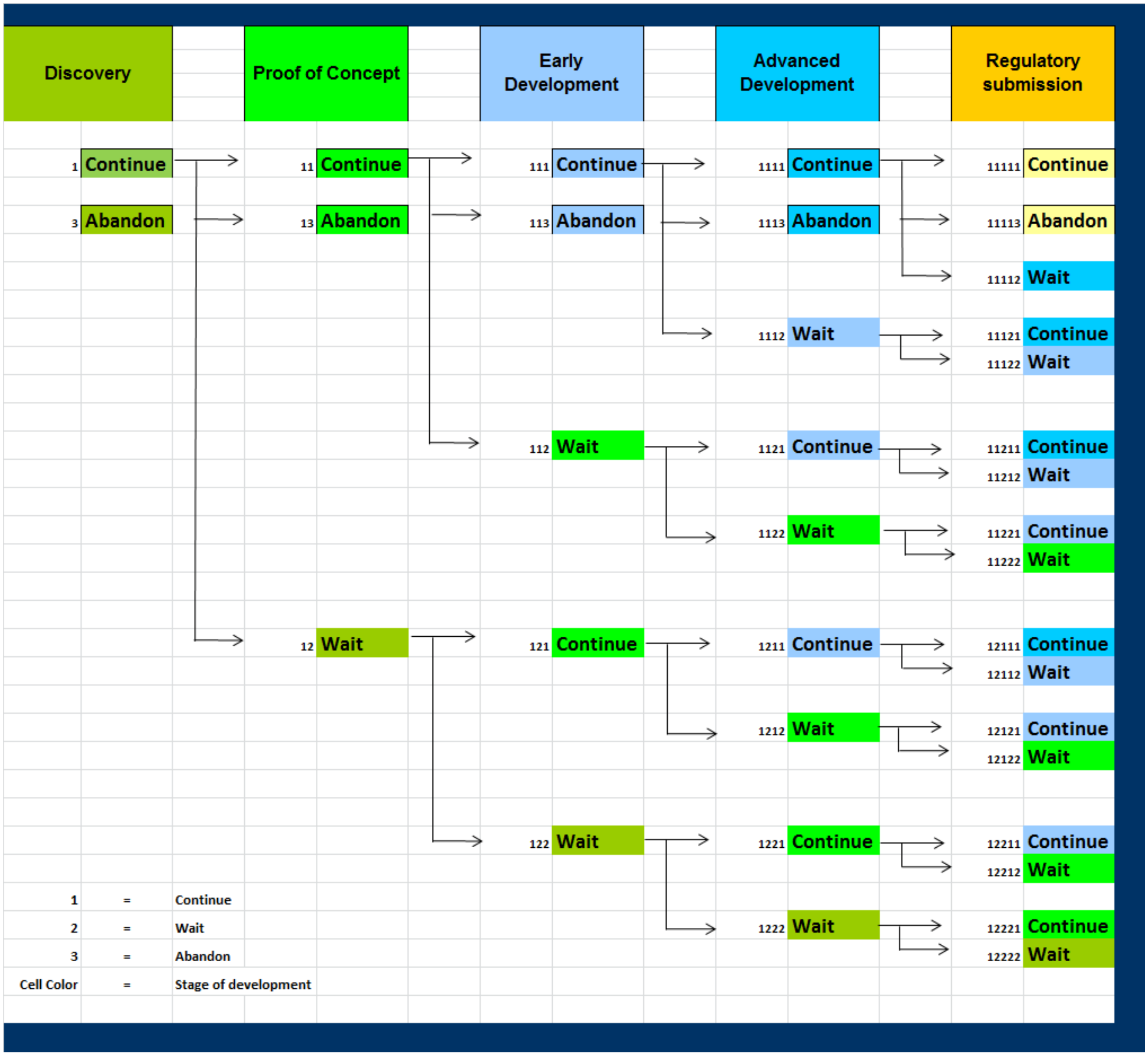


Figure 2. Option Tree for GM Trait Development.

Where Π is the payoff corresponding to upper node u and lower node d, p and (1-p) are probabilities for reaching upper and lower node respectively; and r is risk-free rate of interest. Equation 4 is repeated and the following sequence of equations represents a multi-step binomial model

$$\Pi = e^{-r\Delta t}[p\Pi_{uu} + (1-p)\Pi_{ud}] \quad \text{......Eq. (5)}$$

$$\Pi = e^{-r\Delta t}[p\Pi_{ud} + (1-p)\Pi_{dd}] \quad \text{......Eq. (6)}$$

$$\Pi = e^{-r\Delta t}[p\Pi_{u} + (1-p)\Pi_{d}] \quad \text{......Eq. (7)}$$

Equation 6 is the payoff from the option that can reach the upper node consecutively, or, reach the upper node and then lower node. Equation 7 represents the payoff from reaching the upper node and then lower node or reaching lower nodes twice. Substituting from these equations we get

$$\Pi = e^{-2r\Delta t}[p^2 \Pi_{uu} + 2p(1-p)\Pi_{ud} + (1-p)^2 \Pi_{dd}]$$

......Eq. (8)

The variables p^2, 2p(1-p), and $(1-p)^2$ are the probabilities that the upper, middle and lower nodes will be reached. The option value is equal to its expected payoff in a risk-neutral world discounted to the risk-free rate of interest (Hull, 2004).

The model is an extension of (Jagle, 1999), which developed a real options model for "new product development" case. The net present value of future expected returns (FER) for the agbiotechnology company is calculated from technology fees (TF), planted acres (PA) and projected adoption rate (PAR) and derived over 15 years after commercialization of trait is calculated as:

$$\sum_{i=0}^{n} \mathrm{FER}_t = \mathrm{c} \cdot \mathrm{TF}_t \cdot \mathrm{PA}_t \cdot \mathrm{PAR}_t \cdot (1 / (1 + \mathrm{I}) \wedge \mathrm{T}_t)$$

......Eq. (9)

where: t refers to the year after commercialization, c = technology fee ratio (i.e., share of the trait value charged as a technology fee); TF = technology fee charged (for $i^{th\ year}$) in \$/acre equivalent; PA = planted acres (for i^{th} year) for the crop; PAR = projected adoption rate (for i^{th} year); I = weight adjusted cost of capital ((WACC) = 10 %); T = Time elapsed after trait is commercialized; i = the year after commercialization. The FER for 15 years after commercialization is then used to calculate nodal values of the binomial option tree using backward induction.

The development time and investment costs are treated as random in the binomial option tree. Each phase has a probability that the GM trait would successfully proceed to next phase. The cumulative probabilities are from Monsanto (2008b) and converted into single period probabilities and then treated as risk neutral probabilities to derive the option value at each node (e.g., development phase). The risk neutral probability for any node is solved as:

$$P = \frac{((1+r)^{tp}) * S - S_-}{(S_+ - S_-)}$$

......Eq. (10)

Where: P = risk neutral probability; r = risk free interest rate; tp = time in the phase of development; S = current value of project; S_+ = Present value of cash flow at the end of phase, in case of upward movement and S_- = Present value of cash flow at the end of phase, in case of downward movement.

Monte-Carlo simulation was used to quantify the real option values due to the numerous distributions, some of which are binomial, and some were non-normal. Valuations were derived for individual regions, aggregated to compose a U.S. market value, and then were used to evaluate the logic of the option model. The option values were simulated 10,000 times at which time stopping criteria indicated additional iterations would not improve the results.

Assumptions

Assumptions were made for the analysis and are defined below and in some cases are relaxed in the sensitivities. Trait prices are based on a relation to the value of the trait to growers which are derived from risk premiums. In our base case, we assumed a relative risk aversion of 2 to derive the risk premium. This was relaxed in sensitivity since the distribution of growers' risk preferences is not known. In this sensitivity we derived risk premiums for three different levels of relative risk aversions which were 2, 3 and 4. From these we simulated the trait fees assuming a triangular distribution of trait valuations.

Trait prices are assumed to equal 30% of the value of the trait to the grower, though this is a simplification of a broader more complicated problem of GM pricing.[4] Typically, agbiotechnology companies price traits such that they capture 50% of the value of trait to growers.[5] However, Monsanto indicated a change in strategy and that in the future they would seek to capture 30% of the value of the trait to the grower (Monsanto 2010). Hence, we used the distribution of trait values as shown in Table 1 as the underlying value from which the trait price was defined as .3 of that value. This implies that prices would vary regionally which is a common practice.

Acres planted were defined by USDA crop budget regions and used the percent of acres planted to each region as a point of departure (USDA-NASS, 2010). From this

[4] Further, this research focuses on valuing a single trait, and prices of that single trait. This is much more complicated for stacked traits. See (Gillam, 2011) and (Shi, Chavas, & Stiegert, 2010) who explore pricing stacked traits, and (Magnier, Kalaitzandonakes, & Miller, 2010) .

[5] This is a simple view of a very complicate firm-level optimization problem on trait pricing. Traditionally, the technology fee is defined as ½ the value of the risk premium as defined above (i.e., half of negative exponential utility weighted risk premiums). This is in line with what published news in *Bloomberg* suggests wherein analyst Mark Gulley commented on Monsanto that "They are in essence splitting the value of extra yield 50-50" (Kaskey, 2009). Monsanto has since indicated it will reduce prices for its most expensive crop seeds next year by as much as 75% in a bid to combat market share gains by DuPont.(Kaskey, 2010).

we used an aggregate planted acre of 53.47 million acres with a 5 percent standard deviation**.** The adoption rate was specified as a triangular distribution, the values of which were subjectively determined reflecting data on adoption rates for GM traits (James, 2008) and industry trends. Specifically, penetration increases and reaches a peak in year 7 after introduction, at 70% of the targeted area, and declines thereafter. Adoption of drought tolerant varieties would be insignificant unless there are consecutive years of drought. To incorporate this in the model, the projected adoption rate is correlated with drought occurrence in the prior year. In the case of drought in the previous year, the random draw of adoption rate would tend towards the maximum, else, towards lower half of distribution. The probability of occurrence of drought is modeled as drought coverage area (random) derived from fitted distributions for drought coverage from National Mitigation Center (2010) for each respective region for each of the 15 years after commercialization.

Table 1. Risk Premiums for Drought Tolerant GM Wheat, by Regions and Measures of Trait Efficiency, ($/acre, RRAC=2).

Trait Efficiency	0.2	0.25
Region	$/acre	
Heartland	16.4	20.5
Northern Crescent	6.37	20.44
Northern Great Plains	8.58	10.72
Prairie Gateway	9.2	11.5
Eastern Uplands	2.14	13.71
Southern Seaboard	2.63	3.21
Fruitful Rim	8.74	8.97
Basin Range	3.34	4.18

The salvage value represents the value the company may get by abandoning the project at any stage of development or by licensing it out to other competitors. Since these values are not known, they are evaluated in the simplest (first option tree) scenario wherein salvage option values are all the bottom nodes. Duration and development cost are each random variables and were taken from previous publicly accessible reports (Monsanto, 2008, 2009). The duration of each phase, along with its development cost and probability of success were defined and shown in Table 1.

Table 2. Trait Development Assumptions in Real Option Model Parameters and Distributions.

		Phase of Development				
	Distribution Type	**Discovery**	**Proof of Concept**	**Early Develop-ment**	**Advanced Develop-ment**	**Regulatory Sub-mission**
Time (Years)	Uniform	(2, 4)	(1, 2)	(1, 2)	(1, 2)	(1, 3)
Investment ($million)	Uniform	(2, 5)	(5, 10)	(10, 15)	(15, 30)	(20, 40)
Cumulative Probability	Discrete	0.05	0.25	0.50	0.75	0.90
Single Period Probability	Discrete	0.20	0.50	0.67	0.83	0.90

Source: Monsanto (2008b), Flagg (2008)

Empirical Results

First we show and interpret some of the derived values that are parameters in the real option model. Then, we describe the results from the real option model, managerial interpretation and then show results from some sensitivities.

Derived Inputs for the Real Option Model

An important variable into the *ex-ante* valuation of any GM trait is its valuation. Ultimately, this is the basis of pricing of the GM trait. These were derived using SERF procedures, and interpreted as the certainty equivalence of reduced uncertainty related to use of the GM trait, versus not.

Results are shown in Table 3. These indicate that the greatest value, on a per acre basis in the base case is for Heartland, Northern Crescent, Eastern Uplands, followed by Prairie Gateway and Northern Great Plains. These indicate that the greatest value, on a per acre basis in the base case is for Heartland, Northern Crescent, Eastern Uplands, Prairie Gateway and Northern Great Plains at $6.40, $6.37, $12.14, $9.20 and $8.58 per acre respectively. Strictly, a value of $8.58/acre is the value of the DT trait in the Northern Great Plains and reflects the value of the increased yield and reduced risk associated with the DT trait, versus conventional technology. Thus, in the extreme case if the price of the trait exceeded this value, the grower would choose conventional technology. If the trait price is less than this value, the GM technology would be chosen. These values were derived assuming a RRAC=2.

The change in the risk premium with improvements in trait efficiency is important. Our base case assumes published values in Australia. However, biotechnology companies compete on trait efficiency, ultimately trying to choose events that have greater efficiency than that of their competitors. We simulated impacts of a trait efficiency=.25. In this case, the value of the trait increases by $2 to $4/acre for the major wheat producing regions. This is a very important figure and is an indicator of the prospective increased profitability associated with greater trait efficiency.

Finally, for comparison, values for DT corn using similar methodologies are lesser than those shown here. In corn, the trait efficiency is in the area of .12, versus wheat which is about .20. Thus, for corn, as example in Northern Great Plains, the risk premium for DT is about $6.39/acres, vs. $8.58/acre for wheat indicating the value of improved resistance to drought is apparently much greater for wheat than corn. This is largely driven by the measures of trait efficiency for the traits in the two crops.

Real Option Values of DT Wheat:

Real option values were derived for each phase and for each region. In addition, since this is a stochastic model, the distributional parameters are important. First we describe the aggregate results for each phase. Then, we show the results for each region.

The base case results are shown in Table 3 for both the base case and one with trait efficiency = .25. The results indicate that the real option value is in-the-money at each phase of development. It increases from $12 million at the discovery phase, to $77 million during proof of concept, and ultimately to $419 at the point of regulatory submission. It is of interest that in all simulations the minimum values exceed nil. Thus, the likelihood that the real option value is OTM is nil which would provide substantial confidence about the future payoff.

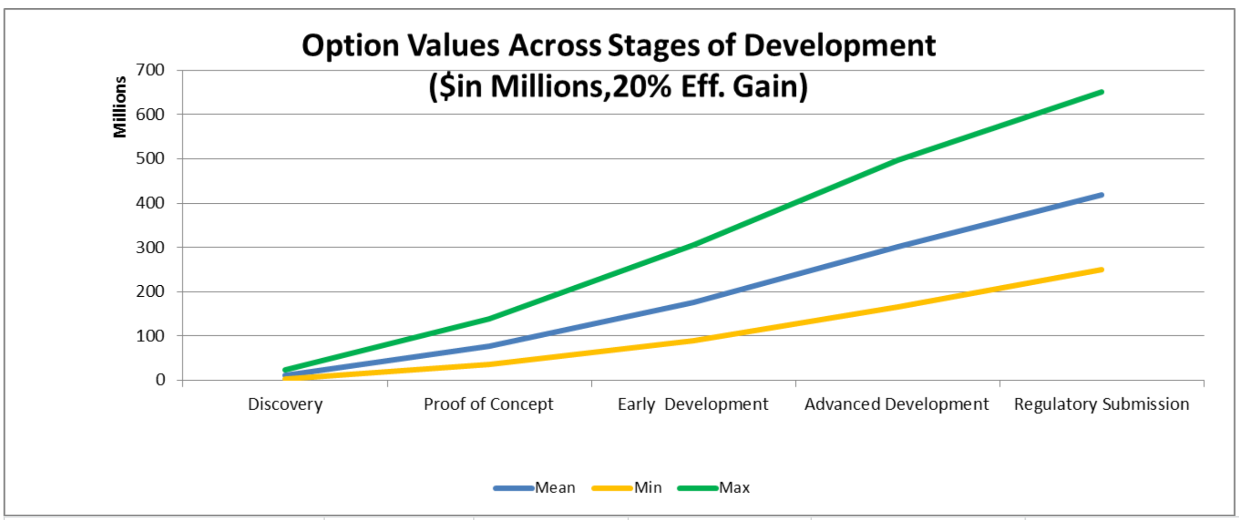
Table 3. Option Value Estimates for Each Phase of Development ($ millions).

		Development Phase				
Trait Efficiency	**Parameter**	***Discovery***	***Proof of Concept***	***Early Development***	***Advanced Development***	***Regulatory Submission***
Base case .20	Mean	12	77	176	301	419
	Min	3	37	90	166	250
	Max	25	139	305	498	651
	StD	3	15	31	49	62
.25	Mean	16	100	227	384	526
	Min	6	50	120	218	316
	Max	31	176	383	623	812
	StD	3	15	31	49	62

Real option values and their distributions across phases are shown in Figures 3 and 4. The distribution of real option values increases as R&D moves through the development phases. This is illustrated in the CDFs (Figure 5) and in the spreads between the minimum and maximum in Figures 3 and 4. Looking forward from the beginning of development, the amount of uncertainty escalates through time. However, both the mean and standard deviation increase through the development phase. The coefficient of variation decreases through the development phase (i.e., from .23 in the discovery phase to .14 at regulatory submission) meaning the greater risk in more advanced phases is offset by a proportionately greater expected real option value.

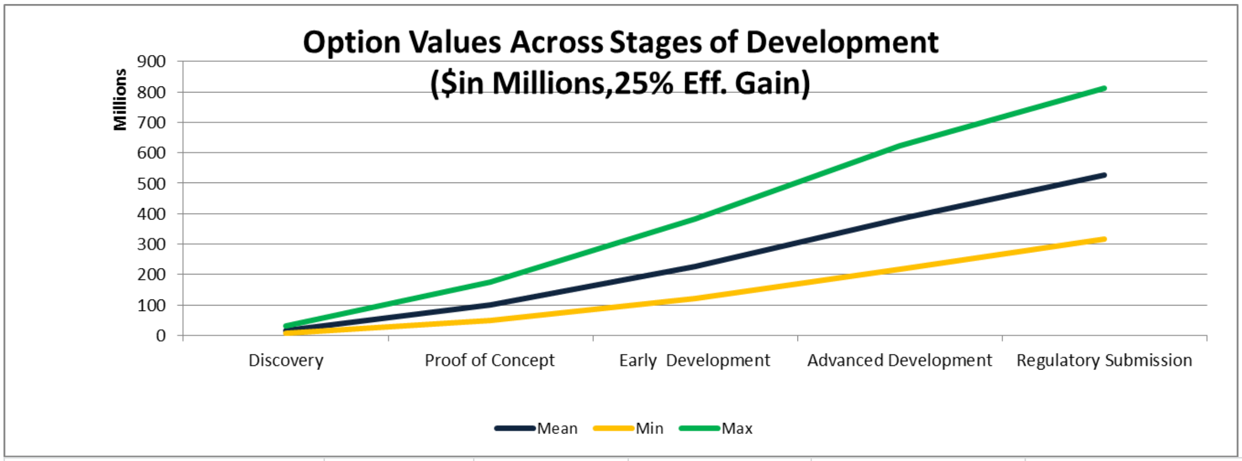
These relationships are also illustrated in Figure 6. Here the vertical axis is the NPV, and the others show the development phases, and the combinations of sequence of options that may be chosen. The option to continue (11111), when chosen consecutively till the last stage of regulatory submission, provides highest return for trait value (Figure 6) at nearly \$419 million. The sequence 11113 is to continue for first four stages and then abandon and the NPV is shown accordingly. The sequence 11121 (a sequence of continue, continue, continue, wait and continue), 11211 and 12111 provide the same final value of \$267 million despite choosing the option to wait at different stages of development. Also note that all three outcomes refer to trait having completed 4th (Advanced development) stage of development (as there are four 1s in them, thus the option to continue was chosen four times).

Real option values for DT wheat were derived for each of the wheat producing regions. These are shown in Table 4 and shown for the final development phase. The regions that would have the greater values are Prairie Gateway and the Northern Great Plains at \$225 and \$266 million respectively. There is no doubt that these are the regions being targeted by the technology companies. Values in all other regions are substantially less.



Simulation 1	0.20				
Drought Tolerance in HRSW	Discovery	Proof of Concept	Early Development	Advanced Development	Regulatory Submission
Min	3,411,179	36,452,322	89,899,279	166,138,437	249,880,718
Mean	12,021,269	76,937,656	176,295,015	301,281,004	418,875,764
Max	24,585,008	138,884,899	304,839,531	497,455,131	651,088,370

Figure 3. Option Values of 'Drought Tolerance' in HRSW Across Stages of Development (Trait Efficiency=.20,,\$ in millions).



Simulation 2	0.25				
Drought Tolerance in HRSW	Discovery	Proof of Concept	Early Development	Advanced Development	Regulatory Submission
Min	5,707,476	49,997,412	120,239,552	217,723,191	315,581,585
Mean	15,897,497	99,964,266	226,526,141	383,457,289	526,425,114
Max	31,096,782	175,877,117	383,274,967	623,391,570	811,641,198

Figure 4. Option Values of 'Drought Tolerance' in HRSW Across Stages of Development (Trait Efficiency=.25, $ in millions).

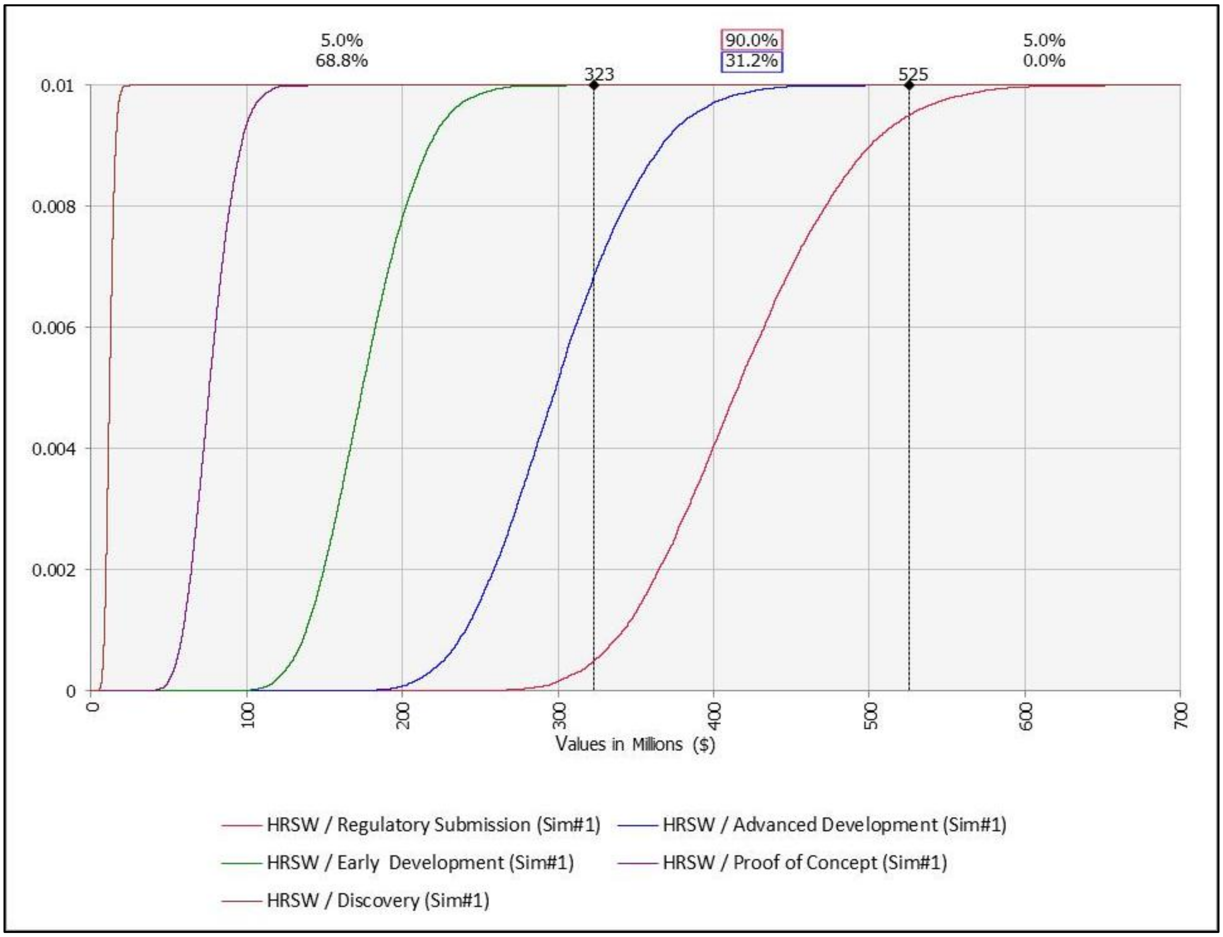


Figure 5. Cumulative Distribution for Option Values of Drought Tolerance Across Stages of Development in HRS for Trait Efficiency= .20 ($millions).

Sensitivities

One of the most important variables that affect the real option value is what we refer to as trait efficiency. For illustration, we ran the model for a trait efficiency of .25 and these results are shown in Tables 3 and 4. The impact of increasing trait efficiency from .2 to .25 is to increase the risk premium to growers, and the real option value to the trait provider. In this case, the real option value increases at each development phase. At the point of regulatory submission, the value increases from $419 to $526 million. Thus, the value of increased trait efficiency is about $107 million to the trait developer. This is a substantial increase in real option value, and hence the reason that trait firms spend so much time identifying the best event, and testing it substantially to verify its efficiency.

Sensitivity was also conducted to determine the random input variables having the greatest impact on variability in the NPV of returns. These are shown in Figure 7 (this is a tornado diagram using regression coefficients from @risk). These results indicate that the most important factors that negatively impact variability in output is the time period for regulatory submission and discovery followed by uncertainty in development. Uncertainty in the technology also has a positive impact on the output variable.

Table 1. Expected Returns by Region

	Efficiency Gain	
	20%	25 %
Region	$ Million	
Heartland	65	82
Northern Crescent	25	32
Northern Great Plains	266	207
Prairie Gateway	225	281
Mississippi Portal	14	17
Southern Seaboard	5	6
Fruit Rim	36	41
B' Range	22	28

Derived as: 1) over 15 years after commercialization; and 2) using a technology fee of 30-50% of the traits value.

The advantage of real option methodologies over NPV procedures is that the option tree captures decisions that management can take at the end of each development stage. The risk associated with distribution of values at each stage is accounted in subsequent stages of development, providing a full potential pathway of option tree for all 'what if' scenarios. Management can therefore directly compare the value of GM trait at any stage without worrying about "had a different combination of option to continue or wait been chosen". For example, it is clear that GM trait development has maximum value if it is allowed to continue at all stages of development. Different combinations and sequence of options to continue and wait have potential to provide next best trait value, which also implies that given different market conditions, decisions can be chosen to maximize the value of trait development. Such comparisons cannot be done using NPV alone.

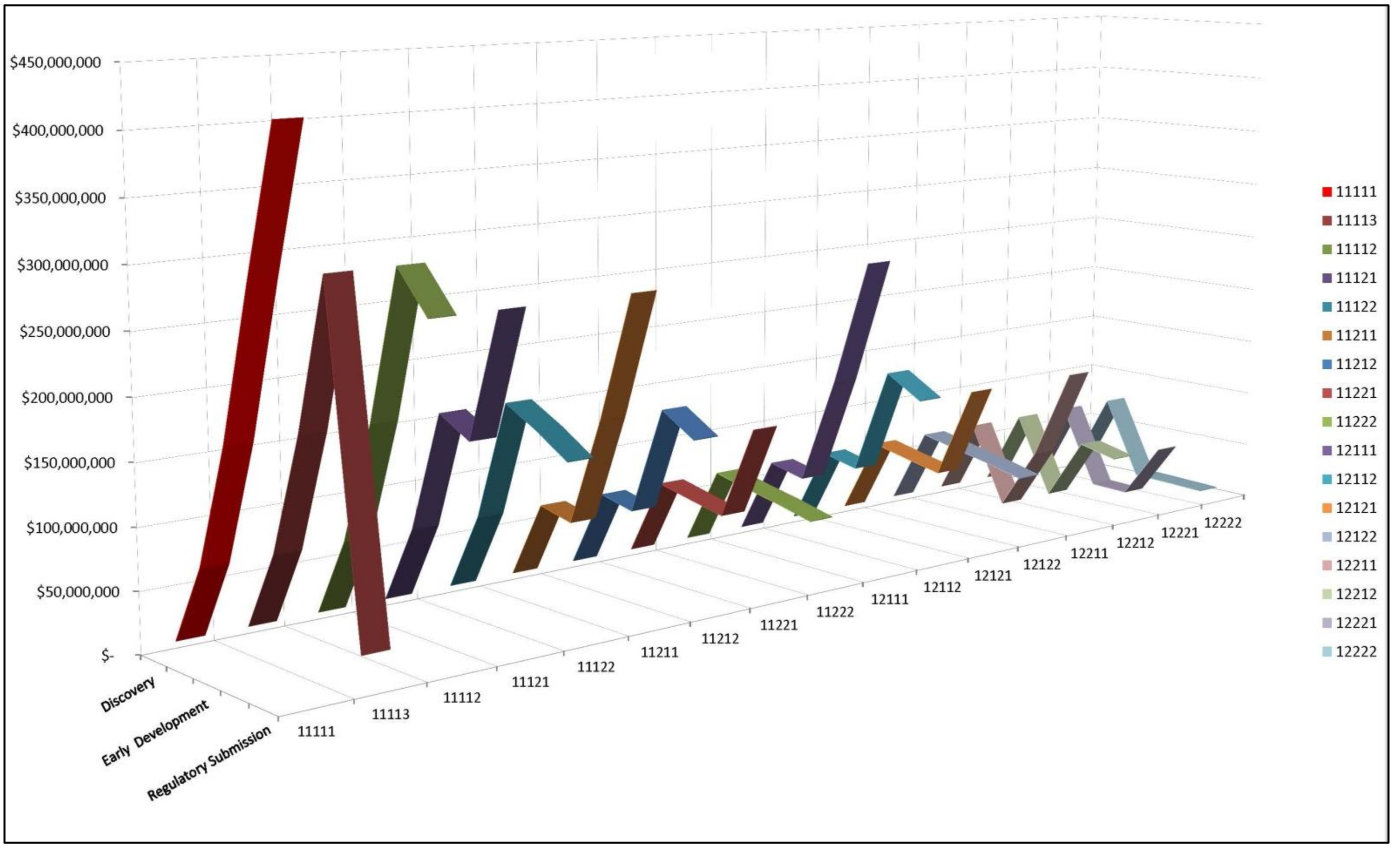


Figure 6. Values from Option Tree for Various Paths Taken (For a Sequence of Option to Continue, Wait or Abandon)

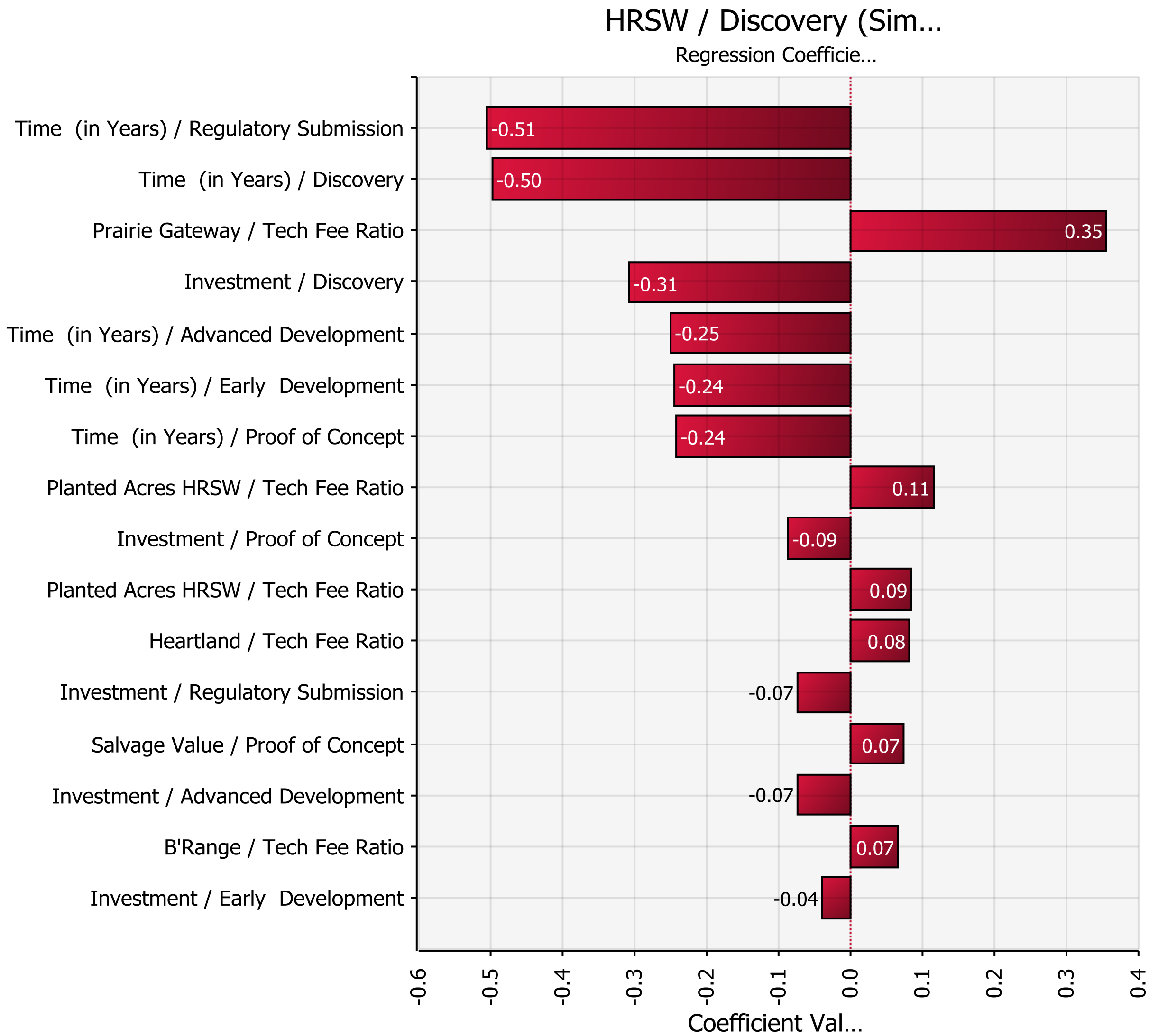


Figure 7. Tornado Results for GM Wheat Trait Development.

Summary and Implications

Wheat has been losing its competitiveness relative to competing crops, particularly those that have access to GM technology, notably corn, soybeans, cotton and canola. Partly in response to this, there has been an increase in grower support for developing GM technology in wheat. Many of the agbiotechnology companies have responded and are all in the process of evaluating and developing traits for this crop. Important in this evaluation is that trait development takes a long period of time, there are many risks associated with development, and it is costly.

The purpose of this paper was to develop an analytical model that could be used to analyze the value of GM traits at different phases of development. To do so we developed a stochastic binomial model of real options. Compared to other studies, this study modeled the private managerial decisions and captured to the extent possible the numerous sources of risks throughout the trait development process.

The results indicate that the value of drought tolerant wheat using GM technology is in the money at each phase of development. Second, the value of GM drought tolerant wheat exceeds that of drought-tolerant corn (Shakya, Wilson and Dahl, 2012). These results no doubt indicate why most of the agbiotechnology companies are developing this trait, amongst others. The greatest value would accrue to the prairie gateway and northern Great Plains regions in the United States, though there would be similar value in numerous other countries which were not the focus of this study. The value of the trait has growing uncertainty throughout the trait development process, looking forward from the inception. However, the variability in NPV diminishes at each phase looking forward. For any probability of success at a developmental stage, the expected value of the trait increases with subsequent stages of development. Also, for a certain value of GM trait, there is less risk associated in later stages of development. A trait that is more likely to be discarded for development such as drought tolerance in initial stages due high probability of being OTM becomes increasingly ITM as the developmental stages pass. The option tree provides the leverage to management to choose the option to wait by recognizing the need of market conditions and still be able to get next best value for the GM trait by deciding to continue later on. Such flexibility is absent when investment decision is made solely on NPV.

There are both public and private implications of these results. From a private perspective, the positive values provide encouragement for further development of this trait. However, the value is not as great as other traits in other crops and as such, this likely means that any variety of wheat would have to have a combination of stacked traits to be commercially acceptable. Finally, that most of the companies are working on similar traits is important. Ultimately, competitive pressures will force companies to strive for the greatest trait efficiency as possible, which as illustrated here, has an important impact on trait valuation. The public implications of these results differ from those of previous studies in part due to the scope of these studies. Here the results indicate positive strategies option values of developing GM traits, in this case, drought tolerance, for wheat. This is encouraging such development, but, in the future as these become commercially available, then many of the issues that are important for post-development commercialization (e.g., as discussed in Carter, Berwald & Loyns 2005; Furtan, Gray & Holzman 2003), strategies for segregating (Wilson & Dahl, 2005), and overall welfare implications of GM wheat (Wilson, DeVuyst, Taylor, Koo, & Dahl, 2008) will become important.

Finally, there are a number of future studies related to the methodologies 00 results here. One is that this trait is being developed for many counties and regions. Results here are for the United States only. Similar methodologies could be used for other regions. Second, similar methodologies could be used to analyze the option values of other traits that are under development as well as future consumer traits. Finally, an important challenge is to analyze the value of stacked traits in a real option framework which seemingly would have to capture the correlation of values and efficiency among traits.

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