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Extreme Events and Land Use Decisions under Climate Change in Tart Cherry Industry in Michigan

Sangjun Lee

Ph.D. candidate, Dept. of Agricultural, Food and Resource Economics
Michigan State University, East Lansing, MI 48824
leesan56@msu.edu

Jinhua Zhao

Professor, Dept. of Economics and Dept. of Agricultural, Food and Resource Economics
Michigan State University, East Lansing, MI 48824
jzhao@msu.edu

Suzanne Thornsberry

Senior Economist, USDA Economic Research Service
355 E Street SW, Washington, DC 20024
sthornsberry@ers.usda.gov

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Extreme Events and Land Use Decisions under Climate Change in Tart Cherry Industry in Michigan

by

Sangjun Lee, Jinhua Zhao and Suzanne Thornsbury

ABSTRACT. This paper studies a land use switching model as a measure of adaptation to climate change in tart cherry industry in Michigan. In order to capture the effects of extreme events, we employ a real options land conversion model where an underlying stochastic process allows a Poisson-type jump component. We compare land use decisions under the increased frequency and severity of extreme weather events as well as well-known gradual climate change. We find that when decision makers are allowed to optimize dynamically and to learn, gradual changes and extreme events can lead to different likelihoods of adaptation occurring as well as different adaptation incentives even when traditional net present value (NPV) calculations are equal. We suggest that although gradual change imposes higher incentive to switch than the extreme events, the realized action may be dominated by the extreme events, especially extreme magnitude change.

Keywords: Climate change, Extreme events, Adaptation, Real options

1. Introduction

Directly exposed to weather conditions, extreme events as well as gradual climate change are often readily translated to crop production, which may end up with imminent crop loss. It is not hard to find such examples in agriculture today. U.S. agriculture faced severe and extensive drought in 2012 for which more than 50 percent of farms and cropland were under the effects as of mid-August 2012 (USDA Economic Research Service 2012). At regional level, we may reach diverse instances of extremes in agriculture beyond well-known drought or flooding. In California unusual rainy days in harvest season reduce both quality and yield of wine grapes due to soggy grapes (Husted 2012).

Evidences of potential increases in effects extreme events are piling up. For instance, premium U.S. wine production is predicted to decline drastically under extreme heat (White et al. 2006). The effects of climate change on major crop yields such as corn, soybean and cotton in the U.S. are also shown to be highly nonlinear functions where temperatures beyond certain thresholds as it can be very harmful to production (Schlenker and Roberts 2009). Specific types of extreme events such as hailstorm damage are not negligible as well (Botzen et al. 2010).

Most remarkably, spring frost in Michigan almost destroyed fruit production in the region in 2012 (De Melker 2012). Among the fruits production in Michigan, tart cherry production in Northwest¹ is most prominent example which is highly sensitive to spring frost events (Winkler et al. 2010). For instance, freeze events after record-high early warm days in the spring of 2012 killed most of cherry buds in this region, which resulted in nearly zero harvest.²

Potential climate change impact in tart cherry industry in Northwest Michigan

In addition to the recent spring frost event, there are some indications in which tart cherry production in the Northwest Michigan may be highly vulnerable to climate change in the future (Winkler et al. 2010). We briefly summarize overview of the industry focusing on potential impact of climate change in the industry.

Gradual change has been recognized widely in agricultural impact assessments and could also be one potential change in tart cherry industry. Some potential drivers have been developing in the industry, which may change yield trend. Wet days during flower/pollination stage are less favorable for pollination rate and tend to lower yields. Some other factors related to fruit quality may indirectly reduce yields by reduce marketable fruits. Wet days during harvest season may increase leaf spot disease (*Coccomyces*

¹ This region includes counties around Traverse City, MI: Grand Traverse, Leelanau, Antrim, Benzie counties. Especially, production sites are highly concentrated in Leelanau and Grand Traverse counties among them.

² Historically, similar spring freeze events occurred in the region in 1945, 1981 and 2002.

hiemalis), which may lead to early defoliation that can result in poor fruit quality in future seasons. Hot and windy weather before harvest may lead to poor fruit quality such as wind whip and soft fruit.

Among extreme events, cold injury to flower bud has been widely addressed in the industry. As cherry trees come out of dormancy in the spring, risk to cold injury increases rapidly since they loosen their cold resistance quickly. Especially, their vulnerability to freeze increases dramatically when trees are at a bud stage, so freeze events followed by warm days may wipe out buds from trees. At least, spring frost events, occurred in 2002 and 2012, have showed empirical signs of change in terms of frequency and magnitude (Zavalloni et al. 2006).

Prior to the 2002 event, significant spring frost only happened in 1945 and 1981. Most growers in the region have taken the event as once in a lifetime situation but another frost event in 2012 may exhibit potential for frequency change in the future. There's a significant sign that trees have come to a development stage earlier in the spring than they were in previous decades. This have widen period of vulnerability to a freeze event in the spring. For example, warm temperature in spring in 2012 drove cherry tree to a development stage about five week ahead of normal (Andresen 2012).

It is noteworthy that spring frost events in 2002 and 2012 quite similar but has some disparate aspects, which can provide new insights in terms of extreme events in the future seasons. While the 2002 event mostly influenced on tart cherry production, the 2012 event has brought even more widespread effects on most fruits (e.g. apples, peaches, sweet cherries and juice grapes) growing mixed with tart cherries in the region. Considering cold weather is normal in the early spring, a few days of warm temperature may not only increase likelihood of the freeze but also broaden the period to be exposed once it happens. Hence, this indicates we may not rule out potentials for severer events in the future.

Adaptations under gradual change vs. extreme events

We argue that extreme events and gradual climate change has remarkably different implication to the phase adaptation. This study applies the real options adaptation model to the tart cherry production in Northwest Michigan for the industry provides us a fertile ground by reflecting most of crucial characteristics in real options framework. In addition to the potential impacts of climate change as discussed above, tart cherry industry, as a perennial crop production, has limited adaptation strategies and require intrinsic investment or establishment costs, which are (partly) irreversible, so that tart cherry growers cannot readily switch their orchards to alternative land use year by year in response to weather conditions. Furthermore, it may not optimal to change land use instantaneously by yearly outcome. Hence, most popular discounted cash flow (DCF) method as a version of net present value (NPV) model does not always reflects the real world pace of adjustment in land use in agriculture (for real option applications

production restructuring problems in agriculture, see Odening, Mußhoff, and Balmann 2005; Hinrichs, Mußhoff, and Odening 2008; Kuminoff and Wossink 2010; Song, Zhao, and Swinton 2011).

We apply a real option land use model where the tart cherry yield follows a jump diffusion process, which is represented as a mixture of continuous variations and discrete jump variations. We compare the effects on land use decisions of three different types of climate change consequences: gradual unfavorable changes in weather patterns, increased frequency of extreme events, and increased magnitude of extremes. The changes are calibrated so that they lead to the same expected losses to the current land use, so that they are equivalent in the traditional cost benefit framework.

More specifically, using historical observed yields, we estimate a jump diffusion model of cherry yields to obtain the parameters of the continuous and jump parts. We then study one drastic form of adaptation: abandoning cherry production altogether to obtain a fixed return (e.g. through selling the land for real estate development). We compare the three climate change consequences in terms of i) the economic incentive to switch, which is represented by optimal switching thresholds and ii) the probability of switching in a given period, which captures realized actions given the thresholds.

2. Decision Making and Timing of Adaptive Actions

2.1 Yield and price processes

Consider a representative tart cherry grower in Northwest Michigan. Assume that the tart cherry production has a stochastic return stream. In order to consider climate and/or weather effects on the land use, we break the return stream into separate stochastic processes: yield and price. We assume that weather conditions and extreme events are reflected in a yield process whereas a price process identifies market adjustments. Finally, we assume operating cost is constant which is non-stochastic. We may write the economic return per unit of land (per acre) from the crop production as

$$\pi_c(t) \equiv \tilde{P}(t)\tilde{Y}(t) - K$$

where $\tilde{P}(t)$ and $\tilde{Y}(t)$ are a unit price (per pound) and yield (pounds per acre) at time t , respectively. Operating cost (per acre) is denoted by K . Let $Y(t) \equiv \ln \tilde{Y}(t)$, then the log yield process, which is assumed to be fluctuating due to weather and/or climate conditions, can be described by the following stochastic process:

$$Y(t) = y + \mu_Y t + \sigma_Y W_Y(t) + \sum_{i=1}^{N(t)} Q_i. \quad (1)$$

where y is the starting point of the process and μ_Y and σ_Y are drift and volatility parameters and $W_Y(t)$ is the standard Brownian motion (Wiener process). Hence, the continuous portion identifies smooth yield variations. The last term in the right hand side (RHS) is a compound Poisson process, which captures rare extreme events. The occurrence of extreme events is represented by a Poisson process $\{N(t)\}$ with arrival rate λ and $\{Q_i\}$ is a sequence of independent identically distributed (i.i.d.) random variables which determines magnitude of extreme events with density $f_Q(q)$. We assume that $W_Y(t)$, $N(t)$ and Q_i are mutually independent.

As the tail behavior of the jump magnitude distribution Q_i determines to a large extent the tail behavior of the probability density of the whole jump diffusion process of $Y(t)$ in equation (1), we can capture distributional features of the impacts of extreme climate events by the density $f_Q(q)$. In theoretical perspectives, the distribution should coincide with a class of yield distributions proposed in the literature. Also, it should capture impacts of extreme events due to climate change empirically.

As a version of exponential-type distributions, we employ exponential distribution in the negative plane as the distribution of the extreme magnitude, which allows only negative jumps as in Mordecki (2002) for option pricing and Egami and Xu (2008) for job switching model. This specification is well-suited under our criteria. First, if we introduce the negative exponential jump size into process in (1), transition density of the yield process becomes close to negatively skewed beta distribution, which is commonly used for crop yield distribution (Goodwin 2009; Hennessy 2011; Nelson and Preckel 1989; Turvey and Zhao 1999). Second, since exponential distribution has higher peak and fatter tail than the corresponding normal distribution, it has an advantage to capture heavy-tail phenomena of climate change impacts. As we rule out positive jumps in the distribution to capture potential losses due to extreme events, we can write the density for jump size as

$$f_Q(q) = \eta e^{\eta q} 1_{\{-\infty, 0\}} \quad (2)$$

where $\eta > 0$ is a jump size parameter so that the smaller η is, the larger is the average magnitude of jump.

Let $P(t) \equiv \ln \tilde{P}(t)$. We assume that changes in logarithmic price does not include jump component but follow a Brownian motion with drift as

$$P(t) = p + \mu_p t + \sigma_p W_p(t) \quad (3)$$

where p is the starting point of the price process and μ_p and σ_p are drift and volatility parameters and $W_p(t)$ is the Wiener process. We assume that the variations in the Gaussian portions of yield and price processes are correlated with each other: $E[dW_Y(t), dW_p(t)] = \rho_{pY} dt$ where ρ_{pY} denotes correlation coefficient between yield and price. Similarly, jump component is assumed to be correlated with the price process $E\left[d\left(\sum_{i=1}^{N(t)} Q_i\right), dW_p(t)\right] = \rho_{pY} dt$.

The smooth price process can be justified from the empirical standpoint of agricultural prices. Agricultural prices may not have jumps at least by four main reasons. First, agricultural products are typically under certain regulations stabilizing prices. For example, tart cherry industry is under Federal Marketing Order which restricts marketable volume when overall production is expected to exceed predetermined amount. Downside price movements have been smoothed out under the order. Second, storage plays a role to stabilize agricultural prices. As the storage acts as a buffer against a short crop year, upside movement has been also smoothed out. Third, prices won't move as sharply as yield variations due to substitution effects. Forth, extreme events don't hit every production region evenly. If we broaden our scope to international production, it is hard to believe that an extreme event occurs at the same time in every growing region all over the world, which indicates international trade may limit price impact due to yield change.

Since both stochastic processes introduced in equations (1) and (3) are special cases of the Lévy process, the equations allow alternative representations using Laplace exponents (Refer Sato 1999 Ch.1 for detail). The log yield and price processes can be represented using the Laplace exponent as

$$\psi_Y(z) = \frac{1}{2} \sigma_Y^2 z^2 + \mu_Y z - \frac{\lambda z}{\eta + z} \quad (4)$$

$$\psi_P(z) = \frac{1}{2} \sigma_P^2 z^2 + \mu_P z. \quad (5)$$

2.2 Land use switching decision

In tart cherry growing area of Northwest Michigan, mostly sandy soil, which is excellent for fruit growing, makes it hard for growers to switch to annual crop production. Furthermore, spring frost event in 2012 signified that switching to another fruit production may not be a good adaptation option. The spring frost in 2002 ran into tart cherry industry while other fruit productions remained moderate in the

region. But similar event in 2012 affected most of fruits productions such as apples or peaches in the region sharply, which makes it hard to rule out the events in the future in those productions, too. Most interestingly, many cherry growing sites located in the shore of Lake Michigan, which has been excellent for tart cherry growing, were major victims of spring frosts due to wind chill from the Lake. Alternatively, these sites provide attractive environments for a real-estate development such as condominiums with high amenity nearby the Lake. With historically high land price, land development other than agricultural use may be a reasonable adaptation option for growers.

Therefore, we study abandoning current land (e.g. through selling land for real estate development) as a feasible adaptation option in the region we consider. We denote sell price of the land to S . Given the log yield and price process defined in (1) and (3), the grower's land use switching problem can be written as

$$\hat{V}(y, p; h) = E^{y, p} \left[\int_0^\infty e^{-rt} [e^{Y(t)+P(t)} - K] dt \right] + E^{y, p} \left[\int_{\tau_h}^\infty e^{-rt} \{ rS - [e^{Y(t)+P(t)} - K] \} dt \right] \quad (6)$$

where τ_h is the hitting time of h such that $\tau_h \equiv \inf \{ t \geq 0 | Y(t) + P(t) \leq h \}$ (refer (Boyarchenko & Levendorskiĭ, 2007: ch. 11 for detail). In the setting above, the first term in the RHS captures value of current system (tart cherry production) without switching. The second term identifies value of switching when $Y(t) + P(t)$ reaches a certain threshold h . Note that selling the land at S is same as constant return stream rS each period.

Since both price and yield are stochastic in our setting i.e. $\pi_c(t) \equiv \tilde{P}(t)\tilde{Y}(t) - K$, economic incentive to switch will depend on relative size of both variables given constant production cost and fixed switching income. Let $\tilde{X}(t) = \tilde{P}(t)\tilde{Y}(t)$ be a gross revenue process. When price is sufficiently high to provide a certain level of $\tilde{X}(t)$, a grower will have less incentive to convert even if yield is low and *vice versa*. Hence, the solution to our problem will depend on the level of gross revenue, which is a function of price and yield. Since price and yield processes are correlated, we may reduce a dimension by constructing the log gross revenue process using the two processes. Define the logarithmic gross revenue process as $X(t) = P(t) + Y(t)$. Then $X(t)$ can be represented as following process

$$X(t) = x + \mu_X dt + \sigma_X dW_X(t) + (1 + \rho_{PY}) \sum_{i=1}^{N(t)} Q_i$$

where $x \equiv p + y$ be the starting point of the log revenue process $X(t)$ and $\mu_X = \mu_p + \mu_y$,

$\sigma_X = \sqrt{\sigma_p^2 + \sigma_y^2 + 2\rho_{py}\sigma_p\sigma_y}$ and $W_X = \frac{1}{\sigma_X}[\sigma_p W_p(t) + \sigma_y W_y(t)]$. Here we need to show that W_X is a

standard Brownian motion. Since W_X is a continuous martingale starting at 0 and

$$\begin{aligned} d[W_X, W_X]_t &= \frac{1}{\sigma_X^2} \left(\sigma_y^2 d[W_y, W_y]_t + 2\sigma_y\sigma_p d[W_y, W_p]_t + \sigma_p^2 d[W_p, W_p]_t \right) \\ &= \frac{1}{\sigma_X^2} \left(\sigma_y^2 + 2\rho_{py}\sigma_y\sigma_p + \sigma_p^2 \right) dt \\ &= dt \end{aligned}$$

where $[\cdot]_t$ denotes a quadratic variation. In the setting the correlation between Gaussian components is reflected in σ_X while the yield jumps are adjusted by the factor $(1 + \rho_{py})$ in the revenue process. That is, if ρ_{py} is negative, which is typical relationship between agricultural price and yield, negative yield shocks are absorbed by price adjustments. Since we know that W_X is the standard Brownian motion, we can represent the (log) gross process above with corresponding Laplace exponent $\psi_X(z)$ as

$$\psi_X(z) = \frac{1}{2}\sigma_X^2 z^2 + \mu_X z - (1 + \rho_{py}) \frac{\lambda z}{\eta + z}. \quad (7)$$

The expected present value (EPV) of switching $\hat{V}(\cdot)$ in equation (6) can be written as a function of x and h :

$$\hat{V}(x; h) = E^x \left[\int_0^\infty e^{-rt} \{e^{X(t)} - K\} dt \right] + E^x \left[\int_{\tau_h}^\infty e^{-rt} \{rS - (e^{X(t)} - K)\} dt \right]. \quad (8)$$

This $\hat{V}(\cdot)$ calculates the EPV of switching in equation (8) from when the log of gross revenue $X(t)$ reaches or crosses an arbitrary threshold level h . In order to study the optimal threshold h^* , we define the normalized expected present value operator \mathcal{E} which calculates the normalized EPV of a stream $g(X(t))$:

$$\mathcal{E}g(x) = rE^x \left[\int_0^\infty e^{-rt} g(X(t)) dt \right]. \quad (9)$$

Introduce the two extremum processes: the supremum process $\bar{X}(t) = \sup_{0 \leq s \leq t} X(s)$ and the infimum process $\underline{X}(t) = \inf_{0 \leq s \leq t} X(s)$ so that $\bar{X}(t)$ and $\underline{X}(t)$ evaluate running maxima and minima of a process

$X(t)$ at time t , respectively. We can define the (normalized) EPV-operators of a function of the supremum and infimum process accordingly:

$$\mathcal{E}^+ g(x) = rE^x \left[\int_0^\infty e^{-rt} g(\bar{X}(t)) dt \right] \quad (10)$$

$$\mathcal{E}^- g(x) = rE^x \left[\int_0^\infty e^{-rt} g(\underline{X}(t)) dt \right]. \quad (11)$$

Note that this switching problem allows same representation with extremum operators as in Boyarchenko & Levendorskiĭ, (2007). Hence, we may write the EPV in (8) as

$$\hat{V}(x; h) = r^{-1} \mathcal{E}(e^x - K) + r^{-1} \mathcal{E}^- 1_{(-\infty, h]} \mathcal{E}^+(rS + K - e^x).$$

Then the optimality condition becomes

$$\mathcal{E}^+(rS + K - e^x) = 0.$$

Define a special version of EPVs applied to the exponential functions

$$\kappa_r^+(z) = rE \left[\int_0^\infty e^{-rt} e^{z\bar{X}(t)} dt \right]. \quad (12)$$

Then solving the optimality condition, we have

$$\mathcal{E}^+(rS + K - e^{h^*}) = rS + K - \kappa_r^+(1)e^{h^*} = 0. \quad (13)$$

For the (log) gross revenue process defined in (7), we can find explicit expressions for $\kappa_r^+(z)$. Define the characteristic equation for the process as $r - \psi_X(z) = 0$, then the equation has unique positive root denoted by β^+ . Then $\kappa_r^+(z)$ has explicit expressions as

$$\kappa_r^+(z) = \frac{\beta^+}{\beta^+ - z}. \quad (14)$$

Plugging this expression into the optimality condition in (13), we have the optimal switching boundary as

$$e^{h^*} = \frac{rS + K}{\kappa_r^+(1)} \Leftrightarrow \tilde{x} = \frac{rS + K}{\kappa_r^+(1)} \Leftrightarrow \tilde{y} = \frac{\beta^+ - 1}{\beta^+} (rS + K) \frac{1}{\tilde{p}} \quad (15)$$

where \tilde{x} , \tilde{p} and \tilde{y} are starting point regular of gross revenue process $\tilde{X}(t)$, price process $\tilde{P}(t)$ and yield process $\tilde{Y}(t)$, respectively.

2.3 Probability of switching: Timing of Adaptation

While the timing of adaptive action may depend on both in price and yield realizations, these movements are reflected in the log gross revenue process. Hence, we only need to study first passage time when $X(t)$ reaches or down-crosses the optimal switching boundary h^* . That is, we consider the probability of switching:

$$P(\tau_{h^*} \leq T) = P\left(\min_{0 \leq t \leq T} X(t) \leq h^*\right) \quad (16)$$

where T is a predetermined time period and h^* is an optimal switching threshold derived above and τ_{h^*} is the first passage time defined by $\tau_{h^*} \equiv \inf \{t \geq 0 \mid X(t) \leq h^*\}$.

Due to undershoot problem (Kou and Wang 2003), we cannot derive explicit form of the distribution of the first passage time. Alternatively, we can derive the Laplace transformation of the first passage time and numerically invert the transformation to obtain probability of switching in a given time T using the following relationship:

$$\int_0^\infty e^{-\alpha T} P(\tau_{h^*} \leq T) dT = \frac{1}{\alpha} \int_0^\infty e^{-\alpha T} dP(\tau_{h^*} \leq T) = \frac{1}{\alpha} E[e^{-\alpha \tau_{h^*}}].$$

Note that we employed exponential distribution for extreme magnitude distribution. Since exponential distribution is a special case of exponential-type distribution, we can obtain explicit form of the Laplace transformation. Let x ($> h^*$) be the starting point of the gross revenue process $X(t)$. For any $\alpha \in (0, \infty)$, the equation $\psi_X(z) = \alpha$ has only two negative roots γ_1 and γ_2 where $\gamma_2 < -\eta < \gamma_1 < 0$. Then the Laplace transform with the jump size distribution in (2) is given by

$$E[e^{-\alpha \tau_{h^*}}] = \frac{\gamma_2(\eta + \gamma_1)}{\eta(\gamma_1 - \gamma_2)} e^{\gamma_1(x-h^*)} + \frac{\gamma_1(\eta + \gamma_2)}{\eta(\gamma_2 - \gamma_1)} e^{\gamma_2(x-h^*)}. \quad (17)$$

For the form of the Laplace transformation given by (17), Gaver-Stehfest algorithm is known to be fast and accurate when inverting the Laplace transformation (See Kou and Wang 2003 for detail). We employ the algorithm to derive the probability of switching in predetermined time period T .

3. Land Use Switching under Climate Change in Tart Cherry Industry in Northwest Michigan

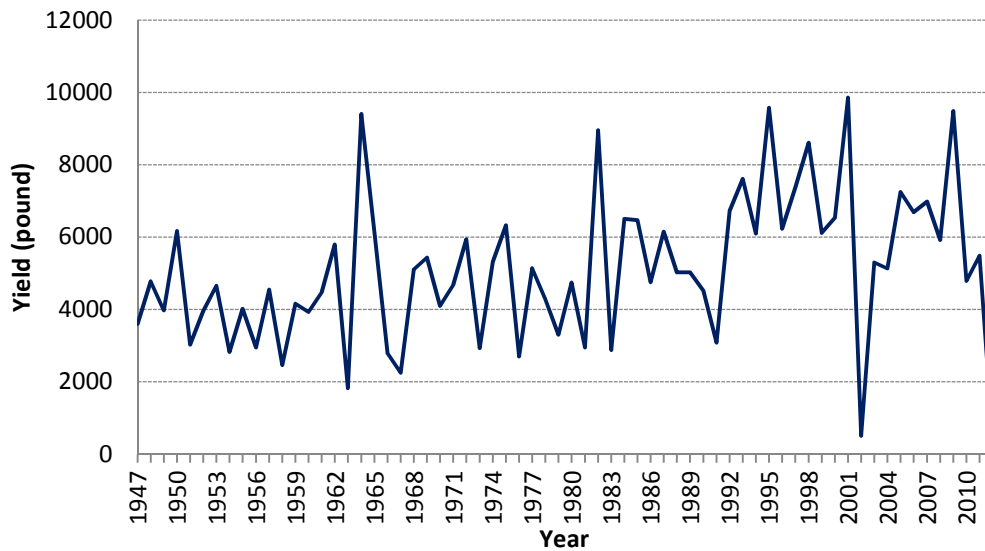
3.1 Data and Estimation

Data

Smaller scale of yield information such as regional specific yield data would be ideal for our application to reflect individual decision-making. Due to data availability, we employ aggregate data and adjust them to reflect production in Northwest Michigan. To estimate stochastic processes of price and yield of tart cherries in the region, yield and price data are taken from Michigan Agricultural Statistics (MASS) for the period of 1947-2012. Since MASS reports the yield and price data with different measure for some years, we calculated them to be yield (pound) per acre and price per pound. In order to deflate the price series, we use CPI for fruit and vegetables obtained from Bureau of Labor Statistics (BLS) since it reflects overall market price changes over time.

Annual tart cherry yield is depicted in Figure 1 and the figure shows that the extreme event in 2002 and 2012 was devastating. The 2002 event was mainly due to wind freeze (28-29°F, northwest wind) within short duration of time (11-12 hours). On the other hand, the 2012 event was induced by early budding due to record-high warm weather, which increased exposure to freezing weather followed by the warmer period.

Figure 1. Tart cherry yield/acre in Northwest Michigan



Annual production costs data are not available for tart cherry production. While there are some surveys for the production costs in Michigan (e.g. Nugent 2003; Black et al. 2010), they are not consistent

each other by relying on different assumptions. We assume that operating cost in our model is constant and we used an estimate in Black et al. (2010) for mid-sized grower in Northwest Michigan (\$688). The annual operating costs consist of i) pruning; ii) mowing; iii) crop protection; iv) herbicide and fertilizer and others. Orchard establishment and land cost are not included and assumed to have already been disbursed.

Since we employ selling the land to be an adaptation option, land value is used to represent the price the grower can receive. Land value is based on the value of farmland for development purposes in the region. We use residential land value of undeveloped land taken from Michigan land value survey in Wittenberg and Wolf (2012). We also assume the land value is constant (\$3,563). When dealing with jump diffusion process as (1), it is not easy to find an asset that duplicates the stochastic dynamics of the process (Dixit and Pindyck 1994). In real options, it becomes even harder to find the replicating asset. Alternatively, we employ risk-adjusted interest rate for the exogenous discount rate r . We assume 6% of risk premium as suggested in Me-Nsope (2009) and McManus (2012). We assume 3.7% for risk-free rate based on recent three year (2010-2012) average of 30 year T-bill rate. Therefore, we use 9.7% risk-adjusted interest rate as a discount rate for our switching problem.

Parameter estimation

We consider logarithmic yield and price processes as given in equations (1) and (3). Primarily, since we assumed the processes to be versions of the Lévy process, which is a continuous time analog of random walk, they would exhibit unit root empirically. Theoretically, Lévy process is right choice for the yield in that it can better reflects trend such as technological progresses as well as extreme events. For the price process, price theory in general suggests that commodity prices are stationary but they often turn out to be non-stationary empirically (Wang and Tomek 2007) due to multiple forces such as structural change, market structure, and macroeconomic shocks. Test results show strong signs in the unit roots for the yield and price processes. Based on augmented Dickey-Fuller (ADF) test, we cannot reject the null hypothesis of the unit root for the log yield process and prices process at the 5% significance level. Intuitively this suggest that Lévy processes (random walks) seems to be more appropriate than other alternatives considering tart cherry market is small with historically high variations of yield and prices.

More importantly, as we model log yield process including jump, we need conduct additional exploratory data analysis on the process. The change in logarithmic yield series $\Delta Y(t)$ should exhibit leptokurtic (fat-tailed) and negatively skewed if the yield process follows the jump diffusion we specified in (1). The skewness and kurtosis of $\Delta Y(t)$ are -0.53 and 8.50, respectively, which exhibit negatively

skewed and fatter-tailed than the normal distribution.³ The change in logarithmic price series $\Delta P(t)$, on the contrary, should be close to normal distribution as we assume Brownian motion in the process. The skewness and kurtosis of $\Delta P(t)$ are 0.04 and 2.74, which seems not away from the normal distribution.

The sample skewness and kurtosis for the yield and price processes naturally lead us to the Jarque-Bera test of normality, which compares sample skewness and kurtosis with those of the standard normal distribution. The test statistic is given by

$$JB = n \left\{ \frac{\hat{\alpha}_{sk}^2}{6} + \frac{(\hat{\alpha}_{ku} - 3)^2}{24} \right\}$$

where n , $\hat{\alpha}_{sk}$ and $\hat{\alpha}_{ku}$ are sample size, sample skewness and kurtosis, respectively. The Jarque-Bera test rejects the null hypothesis of normality for $\Delta Y(t)$ at the 1% level while it does not reject the null for $\Delta P(t)$ even at the 10% significance level. Although the Jarque-Bara test result confirms that $\Delta Y(t)$ is non-Gaussian, the test often performs poorly with small sample and tends to over-reject the null of normality.

Alternatively, we also conduct Shapiro-Wilk test of normality, which is known to have a higher power with small sample. The test statistic is given by

$$SW = \frac{\left(\sum_{i=1}^n a_i X_{(i)} \right)^2}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

where $X_{(i)}$ is the i th order statistic and \bar{X} is the sample mean. The constants a_i are defined by

$$(a_1, a_2, \dots, a_n) = \frac{m' U^{-1}}{(m' U^{-1} U^{-1} m)^{1/2}}$$

where $m = (m_1, m_2, \dots, m_n)'$ are the expected values of i th order statistics of i.i.d. random variables from the standard normal distribution and U is the variance-covariance matrix of the order statistics. Hence, the Shapiro-Wilk test is based on correlation between $X_{(i)}$ and corresponding i th order statistic from the standard normal distribution. Based on the Shapiro-Wilk test, the null hypothesis of normality is rejected

³ The skewness and kurtosis of the standard normal distribution are 0 and 3, respectively.

at the 1% level for $\Delta Y(t)$ while we cannot reject the null for $\Delta P(t)$ even at the 10% significance level. These tests strongly support that $\Delta Y(t)$ is non-Gaussian but $\Delta P(t)$ is Gaussian.

Focusing on an estimation strategy, for a general jump diffusion process, closed-form of probability density function is usually not available. For a jump diffusion model with exponential-type jump, we can approximate the probability density function using its properties (Kou 2002). Changes in logarithmic yield process over time interval Δt is given by:

$$\begin{aligned}\Delta Y(t) &= Y(t + \Delta t) - Y(t) \\ &= \mu_Y \Delta t + \sigma_Y \Delta W_Y(t) + \sum_{i=N(t)+1}^{N(t+\Delta t)} Q_i\end{aligned}$$

where $\Delta W_Y(t) = W_Y(t + \Delta t) - W_Y(t)$. Since $\Delta W_Y(t)$ represent a change in Wiener process, we can deduce that $\Delta W_Y(t)$ has the normal distribution $N(0, \Delta t)$. If the time interval Δt is sufficiently small,⁴ Poisson process can be reduced to Bernoulli distribution within the interval as

$$\sum_{i=N(t)+1}^{N(t+\Delta t)} Q_i \approx \begin{cases} Q_{N(t)+1} & \text{with probability } \lambda \Delta t \\ 0 & \text{with probability } (1 - \lambda) \Delta t \end{cases}.$$

Consequently, the change in log yield process can be approximated in distribution as

$$\Delta Y(t) \approx \mu_Y \Delta t + \sigma_Y Z_Y \sqrt{\Delta t} + B \cdot Q \quad (18)$$

where Z_Y and B are standard normal and Bernoulli random variables, respectively. Q is a random variable whose density is given by (2), i.e. exponential distribution on the negative plane. The density w of the RHS has an explicit expression as

$$w(x) = \frac{1 - \lambda \Delta t}{\sigma_Y \sqrt{\Delta t}} \varphi\left(\frac{x - \mu_Y \Delta t}{\sigma_Y \sqrt{\Delta t}}\right) + \lambda \Delta t \left\{ \eta e^{(\sigma_Y^2 \eta^2 \Delta t)/2} e^{(x - \mu_Y \Delta t) \eta} \Phi\left(-\frac{x - \mu_Y \Delta t + \sigma_Y^2 \eta \Delta t}{\sigma_Y \sqrt{\Delta t}}\right) \right\} \quad (19)$$

where $\varphi(\cdot)$ and $\Phi(\cdot)$ are probability density and cumulative density function of the standard normal distribution, respectively. Setting $\Delta t = 1$ for yearly data, we obtain an estimating equation for the equation (18) given the density (19):

⁴ This condition is to restrict number of jumps in a time interval to be at most one. Though we are applying this approximation to relatively large time interval (yearly data), we allow at most one jump over a year as an extreme event. Hence, the approximation is still valid in our application.

$$\Delta Y(t) = Y(t+1) - Y(t) = \mu_y + \sigma_y Z_y + B \cdot Q. \quad (20)$$

To estimate the parameters of the logarithmic price series, we discretize the equation (3) to estimating equation:

$$\Delta P(t) = P(t+1) - P(t) = \mu_p + \sigma_p Z_p. \quad (21)$$

For the Markov processes including our diffusion models, the maximum likelihood estimation (MLE) has been known to be best choice to estimate parameters as the MLE estimator is asymptotically efficient among all classes of estimators under weak regularity conditions. But the transition density function is rarely available explicitly for general classes of the Markov processes, especially for jump diffusions. As we shown in the equation (19), transition density is approximated explicitly for the jump diffusion model we assumed. For the continuous diffusion model, the transition density is readily available. Since the density functions are given explicitly, we can employ the maximum likelihood estimation (MLE) to estimate parameter of the equations (20) and (21). Finally, the correlation parameter ρ_{py} can be estimated by the sample correlation coefficient of the price and yield processes.

Parameters for the baseline scenario are summarized in Table 1. Overall parameter estimates are statistically not significant at the 5% level. Since only annual yield and price data are available, this problem seems to be inherent due to small sample size. Especially, as we assume jump component as an extreme event which is rare but drastic change, we expect jump frequency λ to be very small. It is not surprising that it is very challenging to attain statistical significance on the parameters associated with jump size and frequency. For example, Bibby, Jacobsen, and Sørensen (2010) show that jump parameters are hard to attain statistical significance considering small number of jumps. However, their simulation study shows that the means of the parameter estimates are very close to the true values. In the same vein, volatility parameters are significant at the 1% level, which reflect higher yearly variations of yield and price well despite small sample size. Estimated correlation coefficient $\hat{\rho}_{py}$ shows high negative correlation (-0.698) between price and yield. It seems natural considering that tart cherry production in the U.S. is highly concentrated in Michigan (70-75% of total U.S. production) so that yields in Michigan determine overall supply in the U.S.

Table 1. Baseline Parameters

Parameters of the stochastic processes of the yields and prices				
	$\Delta Y(t)$		$\Delta P(t)$	
Drift	$\hat{\mu}_Y$	0.072 (0.079)	$\hat{\mu}_P$	-0.001 (0.072)
Volatility	$\hat{\sigma}_Y$	0.580 (0.054)	$\hat{\sigma}_P$	0.582 (0.051)
Jump frequency	$\hat{\lambda}$	0.071 (0.062)		
Jump size	$\hat{\eta}$	0.668 (0.472)		
Correlation	$\hat{\rho}_{PY}$		-0.698	
Operating cost	K		\$688/acre	
Land price	S		\$3,563/acre	

Note: Standard errors are in parenthesis.

3.2 Gradual change and extreme events: climate change scenarios

We consider three different types of climate change consequences: gradual unfavorable changes in weather patterns, increased frequency of extreme events, and increased magnitude of extreme changes. Although these changes may not occur independently in real world, this classification enables us to extract insights concretely by comparing them in terms of an adaptation perspective.

We assume that the three climate change consequences affect yield process defined in (1). The gradual unfavorable change indicates that the production site becomes less favorable smoothly over time due to changing climate conditions. We assume that this change is realized with a change in the drift term. Let $i \in \{m, f, s\}$ to denote gradual, frequency and size change, respectively. Let μ_Y^m be a changed drift term considering gradual climate change effect. The gradual change is captured by $\Delta\mu_Y = \mu_Y^m - \mu_Y$ where $\mu_Y > \mu_Y^m$. The extreme frequency change indicates higher frequency of extreme events such as crop failure, which is assumed to be identified through change in the Poisson parameter by $\Delta\lambda = \lambda^f - \lambda$ where

$\lambda^f > \lambda$. Finally, change in the magnitude of the extreme means that the effect becomes severer on average once an extreme event happens. We assume that the change is captured in the change of jump size parameter. We define the change $\Delta\eta = \eta^s - \eta$ where $\eta > \eta^s$.

As these consequences are not directly comparable, we calibrate then to exhibit equivalent loss in terms of expected present values. These changes are translated into changes in the log gross revenue process $X_i(t), i \in \{m, f, s\}$ as

$$\psi_X^m(z) = \frac{1}{2}\sigma_X^2 z^2 + \mu_X^m z - (1 + \rho_{PY}) \frac{\lambda z}{\eta + z} \quad (22)$$

where $\mu_X^m = \mu_Y^m + \mu_P$. And

$$\psi_X^f(z) = \frac{1}{2}\sigma_X^2 z^2 + \mu_X^f z - (1 + \rho_{PY}) \frac{\lambda^f z}{\eta + z} \quad (23)$$

$$\psi_X^s(z) = \frac{1}{2}\sigma_X^2 z^2 + \mu_X^s z - (1 + \rho_{PY}) \frac{\lambda z}{\eta^s + z}. \quad (24)$$

Let $\Delta EPV_i, i \in \{m, f, s\}$ to be corresponding expected loss from each consequence. By setting $\Delta EPV_m = \Delta EPV_f = \Delta EPV_s$, we can derive equivalent expected loss condition as

$$\begin{aligned} \Delta\mu_Y &= -\frac{1 + \rho_{PY}}{\eta + 1} \Delta\lambda, \\ \Delta\lambda &= -\frac{\lambda}{(\eta^s + 1)} \Delta\eta. \end{aligned} \quad (25)$$

3.3 Empirical results and discussion

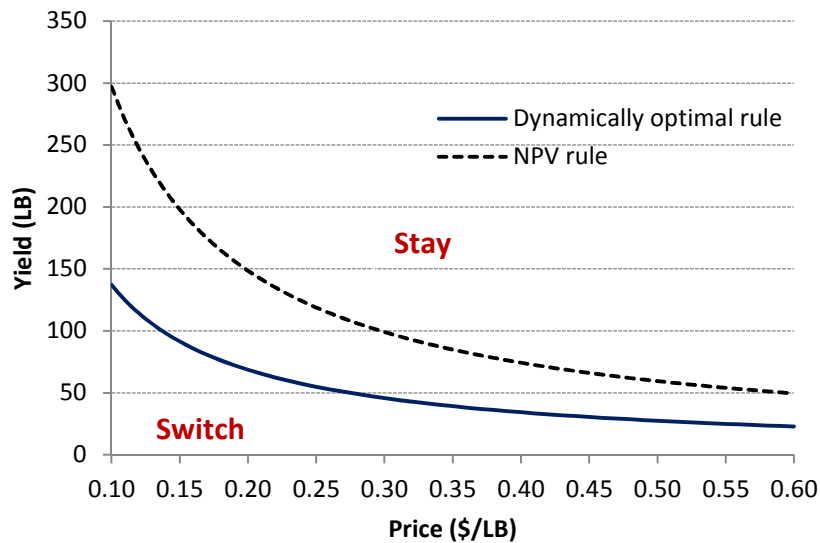
Baseline scenario (without climate change)

Using the estimated coefficient, we first investigate baseline decision rule as given in the equation (15). For convergence of the EPV operator, overall growth rate of gross revenue should be less than assumed discount rate, i.e. $r - \psi_X(1) > 0$. The estimated growth rate of $X(t)$ is 0.16, which is greater than the discount rate. Based on the statistical significance, we set the drift parameters to zero in order to

obtain the convergence, i.e. $\hat{\mu}_Y = \hat{\mu}_P = 0$. Based on the specifications, we derive optimal decision rules portraying optimal switching threshold under dynamically optimal (real option) and NPV rules.

Optimal decision rules are plotted in Figure 2. For a baseline scenario, these rules are derived assuming estimated parameters of price and yield processes stay unchanged in the future (Table 1). The decision rule naturally depends on the price and yield as they are stochastic variables. As the grower faces a set of realized yield and price every year, the grower will make decision to stay or switch. As shown in the figure, the optimal decision rule exhibit inverse relationship between price and yield. Specifically, the grower tends to have a higher incentive to switch facing lower yield and price, *vice versa*. In other words, given price in a year, the grower will have strong incentive to convert if yield is significantly low in which cannot guarantee enough income to stay in the current industry.

Figure 2. Optimal switching thresholds under real option and NPV rule



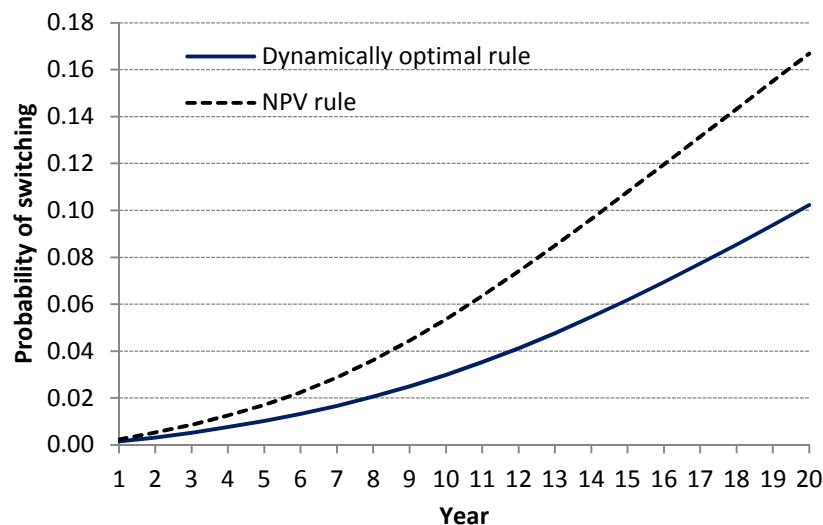
As traditional real option literature indicates (e.g. Dixit and Pindyck 1994), the dynamically optimal real option rule exhibits much stringent threshold than the NPV rule, which shows much less incentive to switch. For example, when price is at 10 cents, the real option rule requires yield is under approximately 150 pounds to decide to switch while the NPV rule indicates it is optimal switch even yield is at 300 pounds at the price. As we pointed out previously, the real option rule reckons with uncertainty, learning and irreversibility for dynamic decision making so that it values more weight on waiting. We also showed that the real option valuation requires evaluating the expected present value based on extreme processes given the stochastic variables while the NPV rule relies on central tendency of the processes. This

naturally leads to more consideration on the tail behavior of the processes, which results in stringent rule in terms of optimal switching threshold.

Given the thresholds, we derive the probability of switching in which a parcel of land in tart cherry production will be sold for residential development during 20 year period, which is known for standard tart cherry orchard lifecycle. The sample average of price and yield level for the period of 1947-2012 are used for initial price and yield for tart cherries to derive the probability. The initial price and yield are calculated as 24cents/pound and 5,488pound/acre, which approximately come to \$1,100 of gross revenue per acre (note: all values are normalized using the CPI).⁵ Since we have the explicit expression of the Laplace transformation of the gross revenue process, we apply the Gaver-Stehfest algorithm to derive the probability. The Figure 3 depicts the probability of switching under the real option and NPV rule.

The probability of switching is increasing with respect to year. As we assume spectrally negative process for the yield process and subsequently for the gross revenue process, it seems natural the probability is increasing since it may be more likely to reach the threshold in the longer time horizon. As the NPV rule sets less stringent boundary of switching, it is highly likely that a grower may convert the land in the longer time horizon. This would result in potential loss by ignoring characteristics associated with the dynamically optimal decision rules.

Figure 3. Probability of switching under real option and NPV rule



⁵ Note that this level is located in the 'stay' area in Figure 2, which is consistent with the grower's current system.

Climate change scenarios

In the Introduction, we briefly discussed about potential yield changes in Northwest tart cherry growing regions which may be in effects in the future due to climate change.⁶ In order to assess climate change effects, we assume extreme frequency is increase by 20% to compare economic decision making under the changes compared to the baseline scenario which maintains estimated parameters. Specifically, the estimated frequency parameter (0.071) is set to change to 20% higher frequency (0.085). While the baseline case indicates approximately one occurrence of extreme event within a 15 year span, the change means the frequency would increase to approximately one occurrence within 12 year period. Considering two spring frost events in Michigan in 10 years, this assumption seems not too drastic. Equivalent gradual change and extreme frequency change are calculated by equation (25). The frequency change above is equivalent to approximately 0.3% yearly decrease in the drift and 71% increase in average size of extreme event, respectively.

In order to investigate robustness of the results provided below, we conduct a sensitivity analysis. For the extreme frequency change ranging from 10-40% with a 5% interval, we derive equivalent gradual and extreme size changes. With the parameter values, we examine the changes in optimal switching boundary and probability of switching. The sensitivity results turn out that the changing pattern in the optimal thresholds and probability of switching are robust under the various set of parameters.⁷

Under the scenarios, we first evaluate changes in optimal threshold to switch. The change is plotted in Figure 4. Since we calibrated each change to have same expected loss, it is not surprising the optimal switching threshold are close each other. Under the equivalent loss condition, we find that real option rule exhibits systematically different economic incentive to switch. Let \tilde{x}^* optimal gross revenue level derived in (15) describing baseline situation to switch. This level indicates that the grower will opt for switching once the gross revenue becomes smaller than the level. For the three climate change consequences, changes in the threshold show clear ranking. The grower will have greater incentive to switch (higher threshold) under the gradual change than the extreme event cases. Between two extreme event cases, the grower will have greater incentive to switch under the frequency change than the magnitude change.

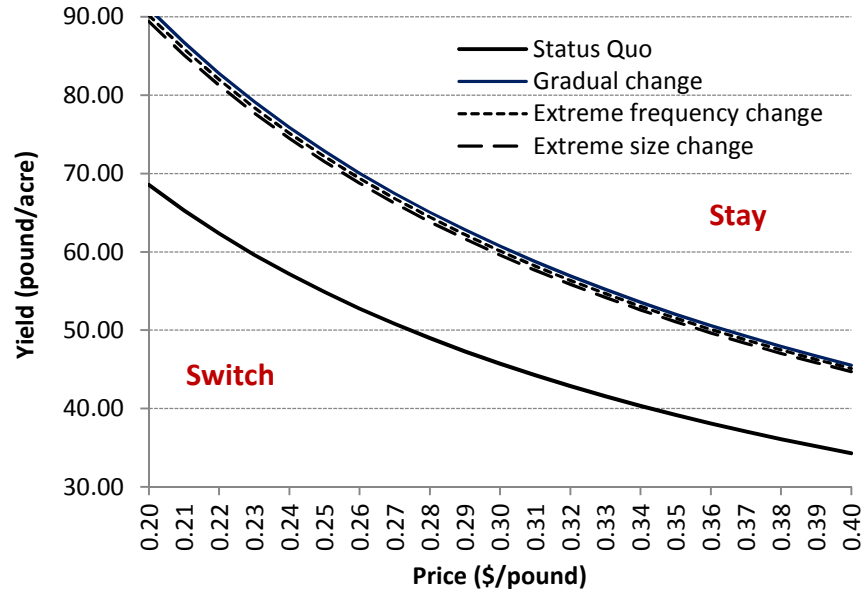
Note that the gradual change, which captured in the deterministic portion, is little to do with uncertainty and learning. Naturally, there is little value of waiting associated with the uncertainty and learning, which induce higher incentive to switch than the extreme events. This is consistent with the

⁶ For future yields under climate change, it is ideal to employ phenologically simulated data under various climate scenarios. While an international research project team for climate assessments is currently evaluating future yields of tart cherries for the Northwest Michigan, the data are not available for use at this time (Winkler et al. 2010).

⁷ Detailed sensitivity analysis results are available upon request.

stylized facts in the real world, and reflects the higher incentive to wait and see under learning patterns represented by a jump process. Between jump frequency and size changes, it is noteworthy that jump size is more closely related to the tail-behavior of given stochastic process. As such, this implies the jump size encompasses higher uncertainty and learning, which give higher incentive to wait and see.

Figure 4. Changes in optimal switching thresholds



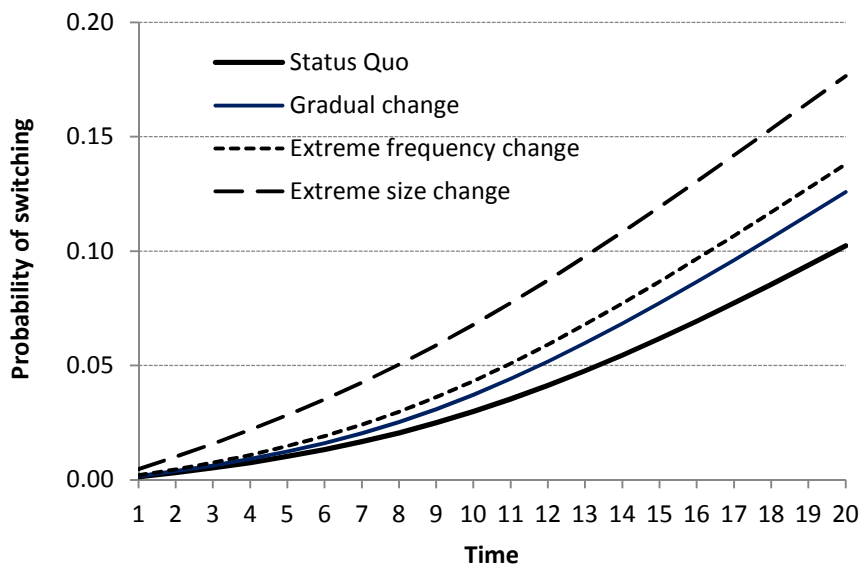
We also compare the realized actions under changes using the probability of switching and the results are reported in Figure 5. For a starting point, we use same point as in the baseline case. Specifically, the sample average of price and yield level for the period of 1947-2012 are used for initial price and yield for tart cherries to derive the probability.

Note that real option decision rule imposes more stringent decision thresholds to extreme event cases than the gradual change. However, the probability of switching implies it is more likely to switch under extreme events despite the lower conversion incentive. This provides an insight about the decision making in the real world. Though the real option theory stresses to disregard temporary or sudden movements in the decision making, the realized action may be dominated by the extreme events. This finding is consistent with another stylized fact: historically most adaptation occurred in response to risks of extreme weather events than the mean changes, e.g. in adopting irrigation technologies (Negri, Gollehon, and Aillery 2005).

Furthermore, the numerical result implies that the contrast between the conversion incentive and conversion probability varies with the time period considered, being more significant in the long run. The

differences in the incentives and probabilities of conversion under the three climate change consequences also increase as the time horizon lengthens. The frequency increase implies that if the time horizon increases, it is highly likely to face at least one occurrence of extreme event. But the size of extreme event may not be sufficiently large to pass the predetermined threshold. The extreme size change, in contrast, if the extreme event comes with larger size one average, one drastic extreme event may easily overshoot across boundary even if the decision rule is set to be very stringent. This pattern signifies the importance of tail-behavior in the decision making in the real world.

Figure 5. Changes in probability of switching



The last findings have important implications for adaptation decisions in the real world: while gradual changes might play a significant role in short-run adaptation decisions, in the long run and all else equal, it is the extreme events that will play a more significant role. For example, considering high concentration in tart cherry industry in Northwest Michigan of total U.S. production, the extreme events may induce significant decline of the industry in the region. This may have strong impacts to the local economy and U.S. agriculture as well. Accordingly, our model has implications designing adaptation policies. Dynamic decision making model we propose shows significant different decision rules than the traditional NPV framework. As climate vulnerability is inherently dynamic process, correctly specifying the dynamic nature in the adaptation policies would be critical. We also propose that there might be clear disparity between economic incentives and realized actions. As extreme events may induce more actions in the long run, our finding stresses the importance of these events for design and implementation of long term adaptation policies.

4. Conclusion

As extreme events due to climate change have been recognized more widely, there are increasing concerns about the extreme events in terms of adaptation. We applied a real option framework to analyze land use switching decision in tart cherry production in Northwest Michigan. Real option decision rule implies that a rational agent may be more reluctant to switch under extreme events. Especially, the optimal switching thresholds under decision rule set most stringent boundary under extreme size change due to higher uncertainty and learning potential around the change. The realized actions, which are represented in terms of the probability of switching in a given time period, exhibit opposite direction compared to the economic incentives. Especially, the probability tends to higher under extreme size change than other changes. This stresses the importance of tail-behavior for the adaptation to climate change in the long run.

Some potential extensions are worth mentioning for further empirical applications. First, as we provide some implications to adaptations to climate change in the industry, especially under presence of extreme events, policy measures need to be investigated. For example, for the tart cherry industry, while revenue based crop insurance scheme is under consideration, there are no policy measures currently in place even with two spring freeze extremes in Michigan in 2002 and 2012. Exploring various policy measures under the framework we proposed can shed lights on finding an efficient policy.

Second, though we find some interesting implications about the effects of extreme events, our empirical application to tart cherry industry do not allow further quantitative interpretations as we rely on assumed scenarios of future climate consequences. In order to infer quantitative implication of climate change based on our framework, a data set describing future yield consequences should be introduced to our model. The phenological data tested under various climate scenarios (e.g. GCMs) would be extremely useful.

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