**2016-16**
**November 2016**


# Working Paper

Charles H. Dyson School of Applied Economics and Management
Cornell University, Ithaca, New York 14853-7801, USA

## Alternative Strategies to Manage Weather Risk in Perennial Fruit Crop Production

Shuay-Tsyr Ho, Jennifer E. Ifft,
Bradley J. Rickard, and Calum G. Turvey

**Alternative strategies to manage weather risk in perennial fruit crop production**[†]

Shuay-Tsyr Ho, Graduate Student
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853, United States

Jennifer E. Ifft, Assistant Professor
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853, United States

Bradley J. Rickard, Associate Professor (contact author)
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853, United States
Tel: +1.607.255.7417
E-mail: bjr83@cornell.edu

Calum G. Turvey, Professor
Charles H. Dyson School of Applied Economics and Management
Cornell University
Ithaca, NY 14853, United States

**Abstract**

Fruit producers in the Eastern United States face a wide range of weather-related risks during the growing season, and many of these events have the capacity to largely impact yields and profitability. This research examines the economic implications associated with responding to these risks for sweet cherry production in three different systems: using high tunnels to protect the crop, purchasing revenue insurance products, and employing weather insurance schemes. The analysis considers a distribution of revenue flows and costs using detailed price, yield, and weather data between 1984 and 2013. Our results show that the high tunnel system generates the largest net return if significant price premiums exist for earlier and larger fruit. Under most conditions, the results also indicate that net returns for the system that uses revenue-based crop insurance exceed those for the system that uses weather insurance products.

*Keywords*: Specialty crops, risk management, crop insurance, weather insurance, high tunnels

*JEL classification*: J43, K37, Q13

---

[†]This research is part of a larger project titled "Enhanced economic sustainability of small farms through the production of stone fruits using mesoclimatic modification technologies" that was funded by the NIFA-USDA Small and Medium Sized Farms Program under grant # 2012-68006-30188. The authors thank Terence Robinson and Greg Lang for valuable input and discussions about the use of high tunnels in fruit production in New York and Michigan.

## Alternative strategies to manage weather risk in perennial fruit crop production

## Introduction

Producing high-value fruit crops in the Northeast and in the Great Lakes region presents both opportunities and challenges for growers. Many of the opportunities are related to the growing trend for local food that has generated direct sales to consumers of more than $1.3 billion nationally in 2012. Of this total, approximately $330 million occurred in Michigan, New York, Massachusetts, Pennsylvania, and Wisconsin, which showcase the importance of local foods in these states (USDA, 2014a). Many of the challenges facing fruit growers in these regions relate to weather risks such as extreme winter temperature events, late-spring frosts, hail, and excess precipitation occurring prior to harvest (Collier et al., 2008).

National participation levels by perennial fruit crop growers in federal crop insurance programs vary from 80% for blueberries to slightly over 50% for apricots, with around 75% for cherries and plums in 2011 (RMA, 2013). As shown in Table 1, the participation levels, measured as acres enrolled in the program as a share of total planted or bearing acres, are more than 50% for most perennial crops in 2014 and the average national participation level is approximately 70%. However, this general trend is not consistent across all states. The participation level for cherries, peaches and pears is relatively low in New York and insurance products are unavailable for pears, plums and strawberries in Michigan. We also observe the availability of high tunnels (sometimes referred to as climatic modification technologies) for fruit and vegetable producers in the Northeast as an alternative risk management tool. High tunnels are used to mitigate weather risks and also enable an extended growing and harvest window which may lead to higher prices for fruit sold in periods with low supply (Lang, 2009). In addition to high tunnels and standard crop insurance products, there is interest among some stakeholders for weather-index based insurance products to hedge against specific weather perils commonly facing specialty crop growers.

Fruit growers are increasingly interested in better understanding how the adoption of high tunnels, compared to market-based tools like crop insurance, will affect yields, local food sales, and farm profitability. Although there is a large literature examining risk management strategies for program crops in the United States, there is very little research that has evaluated the economic implications of adopting various risk management strategies for specialty crop producers (Belasco et al., 2013; Lindsey et al., 2009). The purpose of this research is to develop a framework to evaluate various risk management strategies—including high tunnels, crop insurance and weather insurance—for small- to medium-sized[1] fruit crop growers in the Eastern United States. Our empirical example focuses on fresh sweet cherry production in Michigan and New York State. For each system, we simulate a distribution of prices, yields, and costs over 20 years to consider the typical life cycle of a perennial fruit orchard. We provide results to summarize the net returns to each risk management tool using various criteria to evaluate and rank the different strategies.

**Risk Management for Specialty Crops**

Various unfavorable weather conditions affect specialty crop production, which has led to an increase in the attention given to risk management strategies by growers. Perennial fruit crops in the Northeast are particularly susceptible to a wide range of weather perils. Frost injuries during the bloom period in late spring have severely impacted apples, cherries and grapes in the Northeast in 2002, 2007 and 2012 (Baule et al., 2014). For cherry production, there is also a significant risk associated with fruit cracking due to heavy rainfall just prior to the harvest season (Lang, 2013). Fruit cracking occurs during the fruit ripening stage when excessive water is absorbed through the fruit surface or through the root system and the skin splits or "cracks" (Simon, 2006). Fruit that has cracked due to excessive water is not marketable. Figure 1 presents the frequency of two weather events for sweet cherry production in Michigan and New York between 1984 and 2013. The thick bar show the occurrence of spring frost before and during the bloom stage in Maple City, Michigan measured by degree days on the left vertical axis. The thin lines represent the frequency of excessive rainfall during the harvest season (in Maple City, Michigan and in Sodus Center, New York) measured by precipitation days on the right vertical axis.

The U.S. federal crop insurance program (FCIP) is a safety net that provides *ex ante* protection against price, yield, or revenue risks facing agricultural producers (Barnett, 2014). Participation level and acres insured increased significantly following the Federal Crop Insurance Reform Act of 1994 and the Agricultural Risk Protection Act of 2000. Although the increase in premium subsidies was for both major field crops and specialty crops, the participation level in federal crop insurance program has historically been higher for field crop growers than for fruit and vegetable growers. Acres enrolled in the program as a share of total planted or bearing acres has increased from 17% to 73% between 1990 and 2011 for fruits and nuts; it increased from 16% to 32% for vegetable crops and it increased from 38% to 85% for the major field crops during the same period (RMA, 2013). The revenue-based plans—such as actual revenue history (ARH)—have been implemented on a pilot basis for cherries, navel oranges and strawberries starting in 2009, 2011 and 2012 respectively (FCIC, 2010). Under the ARH policy, historical revenue, rather than historical yield, is insured against losses from yield shortfalls, inadequate market prices, or both.

Since weather insurance payoffs are derived from objective weather outcomes that are caused-oriented, weather insurance reduces the costly administrative and operational expenses associated with monitoring farmer behavior. Such transparency between the insured and the insurer relieves concerns of the adverse selection problem and may lower the transaction costs incurred from asymmetric information between two parties (Barnett, 2014; Moschini and Hennessy, 2001). Given several advantages of weather-index based insurance over conventional crop insurance, weather insurance schemes have been regarded as a potentially effective risk management tool among major program crops (Musshoff et al., 2011; Turvey, 2001; Vedenov and Barnett, 2004). For the application to specialty crops, Turvey et al (2006) developed a unique method to price weather insurance products for ice wine. Fleege et al. (2004) found improved net income from using weather derivative to hedge against heat risk for nectarines, raisin grapes and almonds in California. The use of weather insurance has also attracted the attention of policy makers. Under the Agricultural Act of 2014, subsidized pilot products for weather-index based insurance schemes that are provided by a private insurance company became available in 2015 for crops that have no available insurance products or have low participation rates for existing insurance products (Chite, 2014).

High tunnels are temporary unheated greenhouses that provide a protected environment for various fruits, vegetables, and cut flowers (Carey et al, 2009). Modified growing conditions within the tunnel, via temperature, sunlight, moisture and pest control, may increase marketable yields and enhance fruit quality compared to crops produced in an open-field (Waterer, 2003; Demchak 2009). Furthermore, if the use of high tunnels can effectively extend the harvest window for a crop, it is expected that it will allow producers to capture premium prices for these crops that are available earlier in the season (Cheng and Uva, 2008; Curtis et al., 2014). Others have found that the use of high tunnels may lead to greater net economic benefits compared to crop insurance in the production of oranges and strawberries (Lindsey et al., 2009; Belasco et al., 2013). However, the economic benefits of adopting high tunnels to manage weather risks depend greatly on the premiums that can be expected for higher quality and earlier fruit (Waterer, 2003; Robinson and Dominquez, 2013; Maughan et al., 2015). In addition, in 2009 the Environmental Quality Incentives Program (EQIP) began to provide cost-sharing funds for high tunnel production systems that extend the growing season in an environmentally-friendly and energy-efficient manner (NRCS, 2011).

**Conceptual Framework**

A simulation model is developed to characterize the distribution of revenues and costs associated with the adoption of risk management strategies for sweet cherries in Michigan and New York State. We consider four risk management systems: status quo, high tunnels (the climatic modification technology), revenue-based crop insurance, and weather insurance, and we examine and compare the net returns over a 20-year period in a net present value (NPV) analysis. While an application is made to fresh sweet cherry production in Michigan and New York here, the framework could be used to assess similar questions for other perennial specialty crops in humid continental climate regions where producers have the option to invest in alternative production technologies and available insurance products.

The net returns from risk management strategy $S$ is shown in equation (1), where subscript $r$ denotes a region and subscript $t$ denotes time:

$$\pi_{r,t}^{S} = \underbrace{P_{r,t} \cdot Q_{r,t} - C_{r,t}^{T}}_{\text{net returns from crop sale and production, } NR_{r,t}^{C}} + \underbrace{I_{r,t}^{S}(\phi) - \gamma_{r,t}^{S}}_{\text{net return from insurance participation, } NR_{r,t}^{I}} \qquad r = \text{MI, NY}; t = 1,...,20 \qquad (1)$$

In equation (1), $\pi_{r,t}^{S}$ represents the profit per acre for system $S$, which is comprised of net returns from the harvest, $NR_{r,t}^{C}$, and net returns from purchasing insurance, $NR_{r,t}^{I}$; $P_{r,t}$ and $Q_{r,t}$ are the market price and yield, and its product represents the future gross revenue, $R_{r,t} = P_{r,t} \cdot Q_{r,t}$; production cost, $C_{r,t}^{T} = C_{r,t} + \chi_{r,t}$, is comprised of the cost under the baseline that is held constant under all scenarios, $C_{r,t}$, and the technology cost (the high tunnel in this study), $\chi_{r,t}$, which includes both one-time construction cost of the high tunnel and its associated annual variable cost; $I_{r,t}^{S}$ and $\gamma_{r,t}^{S}$ represent the indemnities and the premiums respectively for different insurance products. In the case of federal crop insurance program, $\phi$ is the level of coverage used to determine the indemnity payout and the associated subsidy. In the analysis of the weather insurance products, $\phi$ represents the weather index used to determine the payout function that insures farmers against the crop loss caused by a specific weather event as well as the premiums.

Uncertainty in future price and production associated with unexpected weather events requires us to carefully consider the stochastic process for prices and yields. Price and Wetzstein (1999) modeled stochastic peach prices and yields, and therefore the stochastic revenue, to determine the optimal entry and exit revenue threshold decision in orchard investment. Richards and Manfredo (2003) priced the revenue insurance for grapes using similar stochastic process for both price and yield. Uncertainty in price, $P$, and yield, $Q$, for sweet cherries could be represented by a geometric Brownian motion process:

$$\frac{dP}{P} = \mu_P dt + \sigma_P dz_P \qquad (2)$$ and

$$\frac{dQ}{Q} = \mu_Q dt + \sigma_Q dz_Q \qquad (3)$$

Where $dP$ and $dQ$ represent the change in per acre price and in per acre tons of fruit, $\mu$ is the drift rate or rate of change in price and yields, and $\sigma$ is the standard deviation. The percentage change in price and yield, $\frac{dP}{P}$ and $\frac{dQ}{Q}$, are normally distributed with mean $\mu T$ and variance $\sigma^2 T$, with increment change in time $T$. The Wiener process, denoted by $dz$, represents the time-independent random shock that follows a standard normal distribution and defines the correlation between variables ($dz_P dz_Q = \rho dt$, $dz_P^2 = dz_Q^2 = dt$), and $\rho$ is the correlation coefficient between price and yield.

Applying Ito's Lemma, the stochastic process of gross revenue, $R = PQ$, follows the geometric Brownian motion (Turvey et al., 2014):

$$\frac{dR}{R} = \frac{\partial R}{\partial P}dP + \frac{\partial R}{\partial Q}dQ + \frac{1}{2}\frac{\partial^2 R}{\partial P^2}dP^2 + \frac{1}{2}\frac{\partial^2 R}{\partial Q^2}dQ^2 + \frac{1}{2}\frac{\partial^2 R}{\partial P \partial Q}dPdQ \tag{4}$$

where $\partial R/\partial P = Q$, $\partial R/\partial Q = P$, $\partial^2 R/\partial P^2 = 0$, $\partial^2 R/\partial Q^2 = 0$ and $\partial^2 R/\partial P \partial Q = 1$. Substituting (2) and (3) into (4) gives the stochastic process for revenue:

$$dR = \mu_R R dt + \sigma_P R dz_P + \sigma_Q R dz_Q \tag{5}$$

where $\mu_R = \mu_P + \mu_Q + \rho\sigma_P\sigma_Q$; $R$ is lognormally distributed such that the percentage change in $R$ over time interval $T$, is normally distributed with mean $\mu_R T$ and variance, $\sigma_R^2 T$, where $\sigma_R^2 = \sigma_P + \sigma_Q + 2\rho\sigma_P\sigma_Q$. By Ito's lemma, the differential of change in logarithm of $R$ over time, $d\ln(R)$, occurs with normally distributed mean $(\mu_R - \frac{1}{2}\sigma_R^2)T$ and variance $\sigma_R^2 T$ (Turvey et al., 2014). Annual forecasted crop revenue could then be derived from the following lognormal Ito's process:

$$R_t = R_{t-1} e^{((\mu_P + \mu_Q - \frac{1}{2}\sigma_P^2 - \frac{1}{2}\sigma_Q^2)dt + N(0,1,\rho)(\sigma_P^2 + \sigma_Q^2 + 2\rho\sigma_P\sigma_Q)^{1/2}\sqrt{dt})} \quad (6)$$

Market price and yield data for fresh sweet cherries in Michigan and New York are available from the USDA's National Agricultural Statistical Service from 1984 to 2013 (NASS, 2015)[2]. Detailed annual cost data for sweet cherry production are not available for Michigan and New York, and therefore we use the data available from California, Washington and Oregon to characterize costs in Michigan and New York State (Grant et al., 2011; Washington State University, 2009; West et al., 2012). In these Western U.S. region, the total per acre costs range from \$9,848 to \$14,456 while the corresponding crop sales per acre range from \$11,900 to \$22,400, and the resulting cost-revenue ratio ranges from 45% to 86%. To generate net return flows in our framework we project future costs by multiplying the gross revenue simulated in equation (6) with an average cost-revenue ratio as shown in equation (7), specific to Michigan and New York respectively,

$$C_{r,t} = R_{r,t} \cdot \left( \frac{\tilde{C}}{\tilde{R}} \right) \quad (7)$$

In equation (7), $\frac{\tilde{C}}{\tilde{R}}$ represents the historical cost-revenue ratio and is multiplied by a specific distribution function that is used as a proxy to characterize the cost and revenue relationship, where $\tilde{R}$ denotes the historical revenue flows. We use Producer Purchase Index for "Other fruits and berries" between 1984 and 2013 (BLS, 2015) to retrieve the historical cost flows, $\tilde{C}$.

**Calculating Net Returns in each System**

The general framework presented in equation (1) is used to quantify the net returns in each system. The forecasted net returns for growers of sweet cherries in region *r* (Michigan or New York) under the baseline (status quo) scenario are simply:

$$\pi_{r,t}^{B} = R_{r,t} - C_{r,t} \qquad (8)$$

Where the simulated gross revenues and costs are calculated following equation (6) and (7) respectively. We expand upon the calculation of net returns in the baseline system to consider specific factors that impact revenues and costs in each of the other three systems.

*High Tunnels*

Relative to the net returns described above, the adoption of high tunnels to mitigate risk will lead to increased costs and potentially higher revenue flows. The calculation of net returns in the system that includes high tunnels is outlined in equation (9):

$$\pi_{r,t}^{T} = \tau \cdot R_{r,t} - (C_{r,t} + \chi_{r,t}) \qquad (9)$$

where $\tau$ represents the revenue multiplier due to improvements in fruit quality, increases in yield, and increases in the per unit price associated with an advanced marketing window. From available experimental data that describe yields and prices for sweet cherries produced under high tunnels in New York during 2010 and 2012, the crop value per acre under the high tunnel system is expected to vary from 1.27 to 3.4 times higher than the crop value without high tunnels. Similar experimental data from research at Michigan State University shows that the value of the crop produced in high tunnels is between 1.3 to 2.5 times higher than the value for fruit produced in an open field[3]. We consider a range of values between 25% and 150% (or equivalent revenue multipliers between 1.25 and 2.50) to describe this premium for fruit produced in a high tunnel.

The cost of establishing high tunnels is approximately $40,000 per acre. While high tunnel structures could remain relatively maintenance free, other variable costs including plastic covers every four years ($4,000 per acre) and annual labor costs for various tasks ($1,200 per acre) are expected (Blomgren and Frisch, 2007). All of these additional costs specific to the high tunnel system are captured in $\chi_{r,t}$.

*Revenue-based Crop Insurance*

Focusing on the ARH pilot program for sweet cherries, the calculation used to determine net returns for a grower adopting crop insurance needs to consider the costs of enrolling in the program as well as the indemnity. Net returns to the grower are outlined in equation (10):

$$\pi_{r,t}^{CI} = \pi_{r,t}^{B} + I_{r,t}^{CI}(\delta_C) - \gamma_{r,t}^{CI} \qquad (10)$$

where $I_{r,t}^{CI}(\delta_C) = Max(\delta_C \cdot \tilde{R}_r - R_{r,t}, 0)$ is the indemnity as a function of the coverage level, $\delta_C$; $\pi_{r,t}^{B}$ is the same as it was defined in equation (8). Approved or certified revenue, denoted by $\tilde{R}_r$, is determined by the historical average of grower revenue based on the past four to ten years, while $R_{r,t}$ is the actual revenue in year *t* and region *r*. In our analysis, we simulate the actual revenue based on yield and price patterns observed between 1984 and 2013. The crop insurance premium is defined by:

$$\gamma_{r,t}^{CI} = E(Max(\delta_C \cdot \tilde{R}_r - R_{r,t}, 0)) \cdot (1 - \zeta(\delta_C)) \qquad (11)$$

For the premium to be actuarially fair, the pre-subsidy premium level is equal to the expected loss or the expected indemnity. The cost of insurance to the grower is determined by subtracting the premium from the subsidy received (denoted as $\zeta$), which, as a percentage of the premium, varies by the level of coverage the grower selects. In our analysis, we consider all the coverage levels from 50% to 75% and subsidies from 67% to 55% (RMA, 2015).

*Weather insurance*

Weather insurance products are indexed to weather variables that are linked to specific events affecting crop size, crop prices, or crop quality. For sweet cherry production in the Northeast and in the Great Lakes region, spring frost and summer precipitation (leading to fruit cracking) are the two main weather risks. A hard frost in the late spring (after the budding process has begun) has the capacity to decrease bud survival through the flowering stage. Tolerance to the freezing temperature varies by stage of development as well as by growing environment and crop types; sweet cherries are relatively vulnerable to frost damage compared to other perennial stone fruit crops such as peaches and plums (Miranda et al., 2005).

Two types of weather-index based insurance programs are considered in our analysis: frost insurance and harvest season rain insurance. The net returns to the grower that adopts weather insurance are described in equation (12).

$$\pi_{r,t}^{WI} = \pi_{r,t}^{B} + I_{r,t}^{WI}(W) - \gamma_{r,t}^{WI}(1-sub), \quad WI = FI, RI;\ W = W_{r,t}^{F}, W_{r,t}^{E}, W_{r,t}^{C} \qquad (12)$$

Here the frost insurance is denoted by $FI$, and harvest rain insurance is denoted as $RI$. The variable $W_{r,t}^{F}$ measures the occurrence of spring frost; $W_{r,t}^{F}$ is the sum of the daily deficit amount in observed temperature falling below the critical thresholds that cause 90% bud kill. Since FCIP began to subsidize weather-index based insurance in 2015, we consider both the unsubsidized and subsidized scenario for weather insurance in our analysis. The subsidy rate is denoted by $sub$ in equation (12); we set it to 0 to consider the case with no subsidy and also consider a range of subsidy rates from 10% to 50%. The indemnity function for frost insurance is:

$$I_{r,t}^{FI}(W_{r,t}^{F}) = \theta_{r}^{F} \cdot W_{r,t}^{F} \qquad (13)$$

where $\theta_{r}^{F}$ is the unit payout growers will receive for each degree deficit. The unknown frost index, $W_{r,t}^{F}$, is approximated by the probabilistic information on potential frost damages, denoted as $\tilde{W}_{r,\tilde{t}}^{F}$, generated using detailed historical weather records from 1984 to 2013 as shown in equation (14).

$$\tilde{W}^{F}_{r,\tilde{t}} = \sum_{s}\sum_{d} \max(T^{C}_{r,s} - \tilde{T}_{r,\tilde{t},s,d}, 0), \qquad \tilde{t} = 1984,...,2013 \qquad (14)$$

Here we use $T^{C}_{r,s}$ to denote the critical temperature at stage $s$ for 90% bud kill, which is commonly used to identify the bud injury at different stages of development (Murray, 2011); $\tilde{T}_{r,\tilde{t},s,\tilde{d}}$ is the daily temperature observed at stage $s$ from 1984 to 2013; $d$ denotes the number of days in each stage.

We consider two types of harvest rain insurance, and develop two indices to capture the effect of summer precipitation: an excess rain index, $W^{E}_{r,t}$, and a cumulative rain index, $W^{C}_{r,t}$. Similar to the design of the frost index, the excess-rain index is characterized by the following indemnity function,

$$I^{RI}_{r,t}(W^{E}_{r,t}) = \theta^{E}_{r} \cdot W^{E}_{r,t} \qquad (15)$$

where $W^{E}_{r,t}$ is measured as the sum of daily rainfall during the harvest season exceeding the threshold that causes fruit cracking; $\theta^{E}_{r}$ is the unit payout growers receive for every excess inch of rainfall. The excess rainfall index, $W^{E}_{r,t}$, is approximated by the probabilistic information on potential excess rain damages, denoted as $\tilde{W}^{E}_{r,\tilde{t}}$, generated using detailed historical weather records from 1984 to 2013 as shown in equation (16).

$$\tilde{W}^{E}_{r,t} = \sum_{d} \max(\tilde{R}_{r,\tilde{t},d} - R^{C}_{r}, 0), \qquad \tilde{t} = 1984,...,2013 \qquad (16)$$

In equation (16), $R^{C}_{r}$ represents the precipitation threshold, $\tilde{R}_{r,\tilde{t},d}$ is the daily precipitation during the period 1984 to 2013, and $d$ denotes the length in days in the harvest season.

The cumulative rainfall index considers the sum of rainfall during the harvest season. Based on the historical precipitation data (Heimfarth and Musshoff, 2011; Skees et al., 2011), the stochastic cumulative rainfall index is specified as:

$$\tilde{W}^{C}_{r,\tilde{t}} = \sum_{d} \tilde{R}_{r,\tilde{t},d}, \qquad \tilde{t} = 1984,...,2013 \qquad (17)$$

which is used to approximate the cumulative rainfall in a given period denoted by $W^{C}_{r,t}$ such that the payoff for the weather insurance is

$$I^{RI}_{r,t}(W^{C}_{r,t}) = \theta^{C}_{r} \cdot \max(W^{C}_{r,t} - \tilde{W}_{r}, 0) \qquad (18)$$

where $\theta^{C}_{r}$ represents the per unit amount the grower will be compensated if the observed accumulated rainfall level goes above the strike level, $\tilde{W}_{r}$.

For all weather insurance products, the actuarially fair premiums are set equal to the expected loss (or the expected indemnity) discounted by a risk-free interest rate, $i$, during time interval, $\Delta t$, if an unfavorable weather event occurs. The calculation of the premium, denoted as $\gamma^{WI}_{r,t}$, is shown in equation (19).

$$\gamma^{WI}_{r,t} = E(I^{WI}_{r,t}(W)) \cdot \exp(-i \cdot \Delta t) \qquad (19)$$

To price the weather insurance products we use detailed data on precipitation and temperature collected over the period 1984 to 2013 from the National Climatic Data Center. The weather data are used to specify late spring frost events and harvest rain events for sweet cherry production regions in Michigan and in New York (NCDC, 2014). Leelanau county and Wayne county are the top sweet cherry producing counties in Michigan and New York respectively; they account for 60% of total bearing acreage in Michigan and for 48% of total bearing acreage in New York (USDA, 2014b). Therefore, we collect the weather data for Maple City, Michigan and Sodus Center, New York as they are located in the representative counties and both have data available over the period from 1984 to 2013.[4]

Given agronomic information that describes the range of dates for specific crop development stages (i.e., green tip and the key bloom dates), we identify the critical times for spring frost (in April and early May) with temperatures that would kill 90% of the buds (Murray, 2011) in the calculation of the frost index. Because the historical data in New York State do not show any cases of temperatures falling below the critical points, we do not consider this type of weather insurance product in New York. Our rainfall indices are generated based on the information that describes the typical harvest windows in late June and early July in both states (NASS, 2006).

In our analysis we set the critical precipitation threshold in the rain index, $R_r^C$, to one inch; the maximum observed level for this index was 2.2 for Michigan and 3.74 for New York. We set the strike level in the cumulative rainfall index, $\tilde{W}_r$, equal to the mean amount of accumulated rainfall between 1984 and 2013. According to the best-fit distribution of historical weather patterns, we use an exponential distribution to characterize all weather-related indices. The per unit payouts for each weather index in each state are set by assuming that, in the worst year, indemnities received by the growers will not exceed 25% of the highest observed level of crop revenue. A series of iterated simulations are then used to determine the prices and the indemnities for the various weather insurance products (Musshoff et al., 2011; Turvey et al., 2006).

**Results**

We employ Monte Carlo simulation techniques to generate the annual net per acre return over a 20-year period from adopting various risk management strategies for sweet cherry production in

Michigan and New York. We consider the effects for a status quo scenario (no risk management strategy) plus four risk management strategies in Michigan, and under the status quo scenario plus three risk management strategies in New York (as weather insurance related to frost is not relevant in New York State). Using an iterative procedure we calculate the net present value per acre for each system at a discount rate of 8% (Song et al., 2011). We also consider other discount rates within a reasonable range and find that it does not change the general thrust of the results we present below. Table 2 shows the key parameters and distribution assumptions for prices and yields (in Michigan and New York) used in the simulation.

A summary of the results for Michigan is presented in Table 3 and a summary of the results for New York is presented in Table 4. The information in the tables summarizes the distribution of net returns to each risk management strategy. We show six levels of revenue premiums (ranging between 25% and 150%) for the fruit produced in the high tunnel system; the premiums are based on the observed revenue premiums for cherries produced in both open field and under high tunnels in field experiments in the two regions. We include six levels of coverage for crop insurance from 50% to 75%, and six subsidy levels for weather insurance from 0 to 50%.

The results in Table 3 show that, in Michigan, the high tunnel system yields the highest expected returns across all the risk management strategies when we assume a high revenue premium for the marketed fruit (at or above 150%). The expected returns to the crop insurance and weather insurance products are greater than the status quo across all the coverage and subsidy levels. The crop insurance strategy provides a relatively high level of expected returns that increase with the coverage level and a relatively low coefficient of variation that remains stable across coverage levels. The coefficient of variation results for the weather insurance products decrease with the subsidy level, indicating that weather insurance would be preferred only when subsidized and as subsidies to the premium increase. Harvest rain insurance generates higher returns compared to crop insurance and compared to high tunnels if we assume low revenue premiums (less than 125%). At the 5$^{th}$ percentile of the net returns distribution, the results show that the crop insurance is preferred to all other risk management strategies and adoption of high tunnels is the riskiest strategy regardless of the revenue premium. At the 95$^{th}$ percentile, the results show that all the strategies generate higher expected returns than the status quo, and that the greatest return occurs with the adoption of the high tunnel system (for all revenue premium levels).

Table 4 shows that in New York State the expected net returns per acre with high tunnels (with a revenue premium at or above 125%) are the highest compared to all other strategies. With either crop insurance across the various coverage levels or with weather insurance (harvest rain insurance) across the various subsidy levels, we see higher net returns than with the status quo scenario. Similar to the results in Michigan, we also see that the crop insurance strategy does not always outperform the weather insurance strategy. Crop insurance leads to higher net returns compared to weather insurance only under the highest coverage level (at 75% coverage). Weather insurance starts to outperform crop insurance with coverage below 60% and when subsidies to premiums exceed 30%. The coefficient of variation is the highest for the high tunnel systems that assume higher revenue premiums. The coefficient of variation is relatively stable (between 2 and 3) among the status quo, crop insurance, and weather insurance scenarios. At the 5$^{th}$ percentile, crop insurance would be the preferred strategy (the option with the smallest negative returns), followed by the status quo and weather insurance; at the 5$^{th}$ percentile, the least preferred strategy is high tunnels. At the 95$^{th}$ percentile, the weather insurance strategy generates higher net returns than the crop insurance strategy; however, overall the high tunnel strategy would generate the highest net return.

**Discussion**

Managing weather risk in the production of specialty crops in humid, cool temperature regions is critical for maintaining fruit quality, ensuring local supply, and generating sustainable profits for growers. The key weather risks involved in growing sweet cherries in Michigan and New York include late-spring frosts (that reduce the quantity of buds) and excessive rain during harvest season (that leads to fruit cracking). Various strategies to mitigate these risks are available and have been considered to some degree by industry stakeholders; these include high tunnels, crop insurance, and weather insurance. The efficacy of different risk management tools varies by region, by producers' attitudes toward risk, as well as by their exposure to weather events. The purpose of this research is to evaluate the long-term economic impacts of adopting the various risk management strategies for sweet cherry production in Michigan and New York. We develop a framework using Monte Carlo simulation methods that will aid farm business managers to make better-informed decisions regarding the adoption of various contemporary risk management tools for specialty crops.

We use historical yield, price, and weather data to simulate the expected net returns under different risk management scenarios. Our findings show that the adoption of high tunnels is the preferred strategy if a relatively large revenue multiplier is assumed.[5] All of the risk management options outperform the status quo system in both Michigan and New York. Overall, the results indicate that a higher revenue premium would be needed in Michigan (relative to New York) in order for the high tunnel system to dominate the insurance-based strategies.

This research adds to the growing body of work that examines risk management issues for specialty crops by focusing carefully on the tools that can be applied to perennial fruit crops in the Northeast and Great Lakes region of the United States. We also contribute to the development of a modeling framework that could be used to study the economics of alternative risk management tools for a range of specialty crops facing substantial risks related to spring and summer weather events. Although we observe an increase in the number of subsidized crop insurance products available for specialty crop growers, it is not clear that such programs are the optimal strategy for managing risk by all fruit and vegetable producers in the Northeast and in the Great Lakes region. Our findings suggest that more consideration should be given to other risk management tools including the high tunnel initiative as part of the EQIP and the pilot weather-indexed based insurance programs for specialty crops as proposed in the Agricultural Act of 2014.

## Endnotes

[1] In 2012, more than 90% of the sweet cherries, tart cherries, peaches, blackberries and strawberries in New York were produced on farms that are less than 25 acres. In Michigan, more than 80% of the sweet cherries, grapes, peaches and strawberries are produced on farms that were less than 25 acres (USDA, 2014b).

[2] The most ideal dataset for yield is at the county- or the farm-level, however, these data are not available for sweet cherries and we use state-level yield data for the simulation analysis. The bearing acreage is only available for total sweet cherry production, therefore the yield per acre is used as a proxy for fresh sweet cherries. Since the price in New York is not disclosed for sweet cherries in fresh utilization, we assume, based on anecdotal evidence from growers, that 90% of sweet cherry production goes to the fresh market.

[3] The high tunnel field data and phenological stage estimates for sweet cherries in New York and Michigan were collected from research trials at the New York State Experiment Station and Michigan State University; detailed information is available upon request.

[4] Using state-level yield data may lead to basis risk that would undermine the accuracy in pricing weather insurance and in empirically identifying the weather-yield relationship to determine the indemnities incurred from specific weather events. Basis risks here refer to both local basis risk and geographical basis risk. Choosing the counties that are the most representative growing regions for sweet cherries in Michigan and New York could reduce the geographical basis risk, however, it is difficult to remove the local basis risk where there exists a stochastic relationship between the specified weather indices and yield variation.

[5] Widespread adoption of high tunnels could increase the availability of early season fruit, and this in turn could reduce the capacity for the system to generate substantial revenue premiums for all producers. Here we assume that any adoption of high tunnels has no such effect and would not have a dampening effect on the potential price premiums.

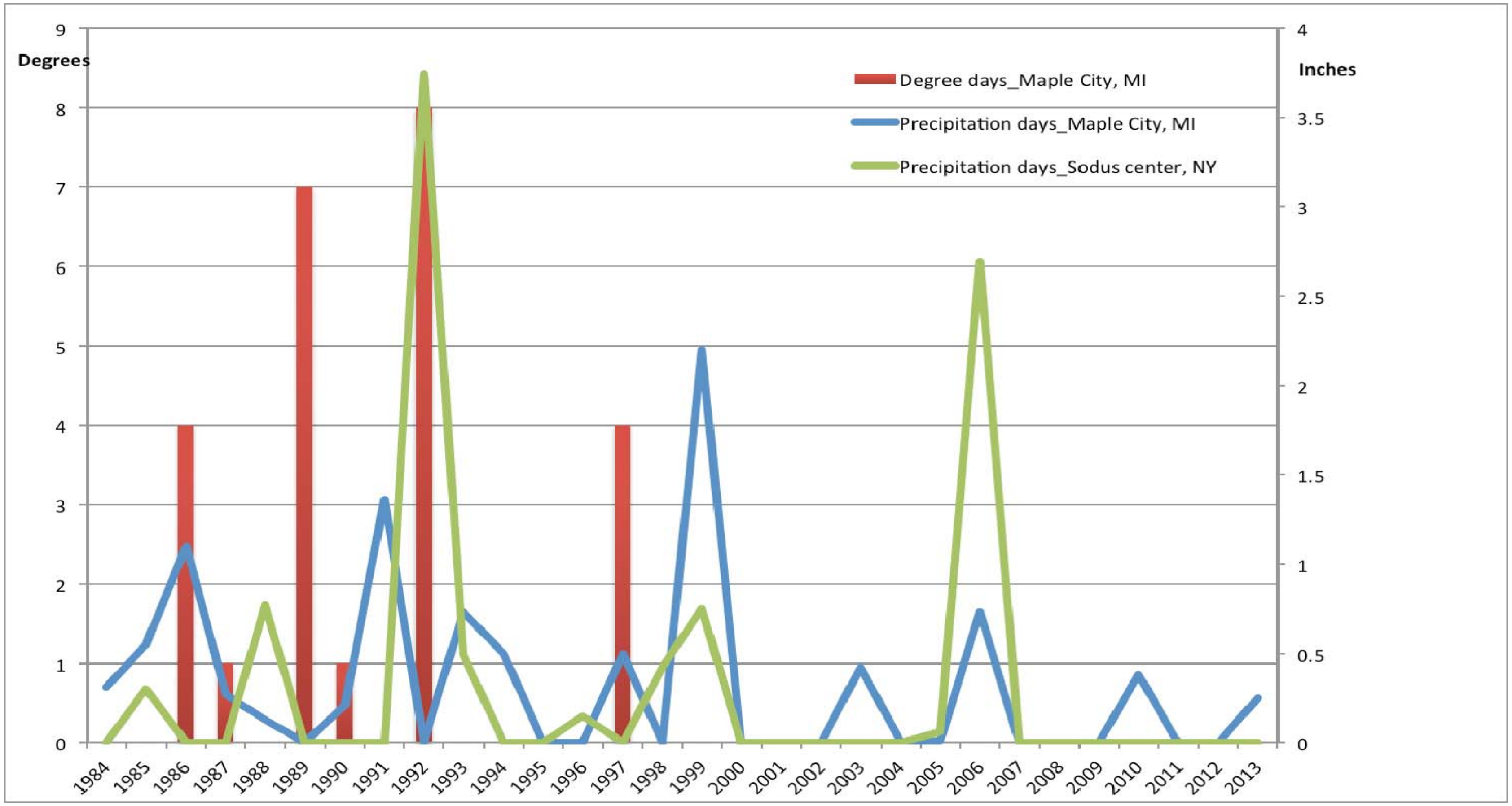


Figure 1. Spring frost and harvest rain events facing sweet cherry growers in Michigan and New York, 1984-2013

Source: NCDC (2014); Murray (2011); NASS (2006)

Note: Degree-days is the sum of the difference in degrees between the critical temperature killing 90% of the buds during the growth stage in late spring and the observed temperature. Precipitation-days is the sum of the difference in precipitation between 1 inch and the observed rainfall.

Table 1. Federal crop insurance for perennial fruit crops: Participation rates and liabilities in 2014

| | | | | | Participation rate: selected states and national level | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | FCIP | RMA acres | Liabilities | NASS acres | California | Washington | Oregon | Florida | Michigan | New York | U.S. |
| Apples | APH | 248,643 | 1,089,063,482 | 327,380 | 0.37 | 0.89 | 0.52 | | 0.78 | 0.81 | 0.76 |
| apricot | APH | 6,251 | 14,327,516 | 10,840 | 0.57 | 0.69 | | | | | 0.58 |
| avocado | APH | 38,209 | 84,425,927 | 59,600 | 0.69 | | | 0.30 | | | 0.64 |
| banana | APH | 409 | 1,486,924 | 900 | | | | | | | 0.45 |
| blueberries | APH | 65,885 | 176,740,045 | 82,630 | 0.76 | 0.49 | 0.28 | 0.60 | 0.67 | N/A | 0.80 |
| boysenberries | | | | 500 | | | N/A | | | | N/A |
| cherries | ARH | 89,248 | 465,331,157 | 127,950 | 0.88 | 0.89 | 0.40 | | 0.53 | 0.24 | 0.70 |
| cranberries | APH | 32,101 | 99,912,594 | 40,500 | | 0.34 | 0.40 | | | | 0.79 |
| dates | | | | 8,200 | | | | | | | N/A |
| figs | APH | 4,076 | 5,820,584 | 7,200 | 0.57 | | | | | | 0.57 |
| peach | APH | 71,813 | 166,306,198 | 102,750 | 0.81 | 0.46 | | | 0.74 | 0.32 | 0.70 |
| nectarines | APH | 16,629 | 34,480,839 | 22,600 | 0.33 | 0.54 | | | | | 0.74 |
| grapes | APH | 604,927 | 1,489,814,925 | 1,049,600 | 0.57 | 0.80 | 0.32 | | 0.73 | 0.56 | 0.58 |
| table grapes | APH | 81,321 | 285,944,613 | 110,000 | 0.74 | | | | | | 0.74 |
| raisins | DOL | | 191891457 | 200,000 | | | | | | | |
| guavas | | | | 100 | | | | | | | N/A |
| kiwifruit | | | | 3,900 | N/A | | | | | | N/A |
| olives | APH | 25,336 | 28,511,163 | 40,000 | 0.63 | | | | | | 0.63 |
| papaya | APH | 57 | 241,573 | 1,300 | | | | | | | 0.04 |
| pears | APH | 33,342 | 97,450,589 | 49,300 | 0.75 | 0.70 | 0.69 | | N/A | 0.05 | 0.68 |
| pecans | PRV | 157,723 | 237,339,887 | N/A | | | | | | | |
| plums | APH | 14,272 | 22,970,621 | 20,500 | 0.74 | 0.54 | 0.45 | | N/A | | 0.70 |
| prunes | APH | 45,798 | 78,590,431 | 48,000 | 0.95 | | | | | | 0.95 |
| raspberries | | | | 18,050 | N/A | N/A | N/A | | | | N/A |
| strawberry | ARH | 26 | 325,080 | 61,310 | 0.001 | N/A | N/A | N/A | N/A | N/A | 0.0004 |
| citrus | APH/DOL /ARH | 669,444 | 1,117,368,802 | 782,300 | 0.85 | | | 0.87 | | | 0.86 |
| walnut | APH | 148,493 | 349,109,949 | 290,000 | 0.51 | | | | | | 0.51 |
| hazelnut | | | | 30,000 | | | N/A | | | | N/A |
| almond | APH | 720,494 | 2,187,339,139 | 860,000 | 0.84 | | | | | | 0.84 |
| pistachio | APH | 92,172 | 295,237,074 | 215,000 | 0.42 | | | | | | 0.43 |
| macadamia nuts | APH | 11,934 | 18,957,463 | 160,000 | | | | | | | 0.07 |
| **Total** | | 3,178,603 | 8,538,988,032 | 4,730,410 | 0.62 | 0.80 | 0.28 | 0.84 | 0.66 | 0.64 | 0.72 |

Source: Aggregate data from RMA (2014) and NASS (2014, 2015)
Note: An empty cell indicates that the state does produce (or produces very little) of the crop; N/A indicates that the state does produce the crop but that crop insurance is not currently available.

Table 2. Baseline parameters used in the Monte Carlo simulation analysis

| Simulation parameters | | Original data | | Brownian motion process | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Mean | Standard deviation | Initial Value (2013) | Drift | Volatility | Correlation | Cost-revenue ratio |
| Michigan | price | 2300 | 584.94 | 2290 | 0.033 | 0.029 | -0.43 | Lognormal |
| | yield | 2.97 | 0.96 | 3.47 | -0.01 | 0.737 | | |
| | revenue | | | 7946 | -0.245 | 0.725 | | |
| New York | price | 2210 | 768.86 | 3370 | 0.054 | 0.185 | -0.51 | Triangle |
| | yield | 1.52 | 0.51 | 1.49 | -0.01 | 0.43 | | |
| | revenue | | | 5587 | -0.068 | 0.374 | | |

Table 3. Summary statistics for the NPV results in Michigan ($/acre)

| System | | Expected value | CV | Median | Skewness | Distribution percentile 5th | Positive | | 95th |
|---|---|---|---|---|---|---|---|---|---|
| Status quo | | 4,956 | 8 | 2,778 | 20 | -16,148 | 30th | 516 | 27,738 |
| High tunnel | | | | | | | | | |
| *Revenue* | 25% | -44,771 | -6 | -53,280 | 8 | -166,497 | 85th | 3,245 | 97,560 |
| *Premium* | 50% | -32,808 | -7 | -48,449 | -11 | -162,003 | 85th | 19,425 | 139,962 |
| | 75% | -17,233 | -26 | -43,477 | 45 | -156,011 | 80th | 9,956 | 170,809 |
| | 100% | -9,270 | -34 | -38,530 | 11 | -147,693 | 75th | 5,154 | 210,041 |
| | 125% | 5,368 | 71 | -32,818 | 19 | -145,986 | 70th | 2,300 | 251,254 |
| | 150% | 18,935 | 31 | -28,766 | 63 | -140,795 | 70th | 11,511 | 284,341 |
| Crop Insurance | | | | | | | | | |
| *Coverage level* | 75% | 11,435 | 5 | 6,134 | 30 | -10,567 | 20th | 937 | 43,378 |
| | 70% | 11,088 | 5 | 6,216 | 29 | -10,647 | 20th | 1,152 | 41,765 |
| | 65% | 10,309 | 6 | 5,819 | 28 | -11,256 | 20th | 838 | 39,654 |
| | 60% | 9,667 | 6 | 5,540 | 28 | -11,629 | 20th | 642 | 38,180 |
| | 55% | 9,190 | 6 | 5,398 | 27 | -11,909 | 20th | 527 | 36,617 |
| | 50% | 8,639 | 6 | 5,169 | 26 | -12,440 | 20th | 368 | 35,216 |
| Frost Insurance (Degree days) | | | | | | | | | |
| *Subsidy* | 0% | 5,688 | 12 | 257 | 31 | -15,998 | 50th | 257 | 33,589 |
| | 10% | 6,203 | 11 | 772 | 31 | -15,483 | 45th | 10 | 34,104 |
| | 20% | 6,718 | 10 | 1,287 | 31 | -14,968 | 45th | 525 | 34,619 |
| | 30% | 7,233 | 9 | 1,802 | 31 | -14,453 | 40th | 369 | 35,133 |
| | 40% | 7,748 | 9 | 2,316 | 31 | -13,938 | 35th | 188 | 35,648 |
| | 50% | 8,262 | 8 | 2,831 | 31 | -13,424 | 30th | 31 | 36,163 |
| Harvest rain insurance (Precipitation days) | | | | | | | | | |
| *Subsidy* | 0% | 5,951 | 12 | -723 | 29 | -16,355 | 55th | 162 | 36,597 |
| | 10% | 6,667 | 11 | -7 | 29 | -15,639 | 55th | 878 | 37,313 |
| | 20% | 7,383 | 10 | 709 | 29 | -14,923 | 50th | 709 | 38,029 |
| | 30% | 8,099 | 9 | 1,425 | 29 | -14,207 | 45th | 586 | 38,745 |
| | 40% | 8,815 | 8 | 2,142 | 29 | -13,491 | 40th | 559 | 39,461 |
| | 50% | 9,531 | 8 | 2,858 | 29 | -12,775 | 35th | 562 | 40,177 |
| Harvest rain insurance (Cumulative rainfall) | | | | | | | | | |
| *Subsidy* | 0% | 5,789 | 13 | -812 | 29 | -16,686 | 55th | 37 | 35,917 |
| | 10% | 6,520 | 11 | -81 | 29 | -15,956 | 55th | 767 | 36,647 |
| | 20% | 7,250 | 10 | 649 | 29 | -15,226 | 50th | 649 | 37,377 |
| | 30% | 7,980 | 9 | 1,379 | 29 | -14,495 | 45th | 543 | 38,107 |
| | 40% | 8,710 | 8 | 2,109 | 29 | -13,765 | 40th | 556 | 38,837 |
| | 50% | 9,440 | 8 | 2,840 | 29 | -13,035 | 35th | 511 | 39,568 |

Table 4. Summary statistics for the NPV results in New York ($/acre)

| | | Expected | | | | Distribution percentile | | | |
|---|---|---|---|---|---|---|---|---|---|
| System | | value | CV | Median | Skewness | 5th | Positive | | 95th |
| Status quo | | 5,775 | 2 | 3,720 | 8 | -3,487 | 20th | 415 | 20,707 |
| High tunnel | | | | | | | | | |
| *Revenue* | 25% | -39,266 | -3 | -49,168 | 6 | -152,820 | 85th | 15,231 | 98,106 |
| *Premium* | 50% | -23,926 | -6 | -39,917 | 20 | -141,579 | 75th | 404 | 132,562 |
| | 75% | -12,501 | -10 | -31,263 | 4 | -133,557 | 70th | 2,537 | 165,987 |
| | 100% | 1,085 | 130 | -21,376 | 5 | -126,591 | 65th | 3,778 | 193,095 |
| | 125% | 16,846 | 10 | -12,776 | 6 | -122,315 | 60th | 4,647 | 245,422 |
| | 150% | 28,941 | 6 | -3,908 | 6 | -113,837 | 55th | 5,183 | 267,428 |
| Crop insurance | | | | | | | | | |
| *Coverage level* | 75% | 7,616 | 2 | 4,962 | 8 | -2,214 | 15th | 594 | 25,224 |
| | 70% | 7,353 | 2 | 4,817 | 8 | -2,308 | 15th | 511 | 24,154 |
| | 65% | 7,004 | 2 | 4,595 | 8 | -2,512 | 15th | 357 | 23,256 |
| | 60% | 6,781 | 2 | 4,487 | 8 | -2,655 | 15th | 312 | 22,580 |
| | 55% | 6,505 | 2 | 4,277 | 8 | -2,884 | 15th | 165 | 21,917 |
| | 50% | 6,307 | 2 | 4,142 | 8 | -3,003 | 15th | 49 | 21,429 |
| Harvest rain insurance (Precipitation days) | | | | | | | | | |
| *Subsidy* | 0% | 5,845 | 3 | 2,382 | 10 | -4,571 | 35th | 497 | 25,622 |
| | 10% | 6,164 | 3 | 2,700 | 10 | -4,252 | 30th | 224 | 25,941 |
| | 20% | 6,482 | 2 | 3,019 | 10 | -3,934 | 30th | 543 | 26,259 |
| | 30% | 6,800 | 2 | 3,337 | 10 | -3,615 | 25th | 237 | 26,578 |
| | 40% | 7,119 | 2 | 3,656 | 10 | -3,297 | 25th | 555 | 26,896 |
| | 50% | 7,437 | 2 | 3,974 | 10 | -2,979 | 20th | 265 | 27,214 |
| Harvest rain insurance (Cumulative rainfall) | | | | | | | | | |
| *Subsidy* | 0% | 5,874 | 3 | 2,372 | 11 | -4,563 | 35th | 514 | 25,806 |
| | 10% | 6,191 | 3 | 2,690 | 11 | -4,245 | 30th | 249 | 26,123 |
| | 20% | 6,508 | 2 | 3,007 | 11 | -3,928 | 30th | 566 | 26,441 |
| | 30% | 6,826 | 2 | 3,325 | 11 | -3,610 | 25th | 245 | 26,758 |
| | 40% | 7,143 | 2 | 3,642 | 11 | -3,293 | 25th | 562 | 27,075 |
| | 50% | 7,461 | 2 | 3,959 | 11 | -2,976 | 20th | 279 | 27,393 |

## References

Barnett, B., 2014. Multiple-peril crop insurance: successes and challenges. Agricultural Finance Review. 74(2), 200-216.

Baule, W., Gibbons, E., Briley, L., and Brown, D. 2014. "Synthesis of the Third National Climate Assessment for the Great Lakes Region". Great Lakes Integrated Sciences + Assessments (GLISA). Graham Sustainability Institute, University of Michigan. Available at: http://glisa.umich.edu/media/files/Great_Lakes_NCA_Synthesis.pdf (Accessed October 2016)

Belasco, E., Galinato, S., Marsh, T., Miles, C., and Wallace, R., 2013. High Tunnels Are My Crop Insurance: An Assessment of Risk Management Tools for Small-scale Specialty Crop Producers. Agricultural and Resource Economics Review. 42(2), 403–418.

Blomgren, T., and Frisch, T. 2007. High Tunnels: Using Low Cost Technology to Increase Yields, Improve Quality, and Extend the Season. Center for Sustainable Agriculture, University of Vermont.

Bureau of Labor Statistics, U.S. Department of Labor, 2015. Producer Price Index Commodity Data: Other fruits and berries, 1984-2013. BLS, Washington, DC. Available at: http://data.bls.gov/pdq/querytool.jsp?survey=wp (Accessed January 2015).

Carey, E. E., Jett, L., Lamont, W. J., Nennich, T. T., Orzolek, M. D., and Williams, K. A., 2009. Horticultural crop production in high tunnels in the United States: A snapshot. HortTechnology, 19(1), 37-43.

Cheng, M., and Uva, W., 2008. Removing Barriers to Increase High Tunnel Production of Horticultural Commodities in New York. Economic and Marketing Study Final Report.

Chite, R.M. 2014. The 2014 Farm Bill (P.L.113-79): Summary and Side-by-Side. Congressional Research Service: CRS Report for Congress. R43076.

Collier, R., Fellows, J. R., Adams, S. R., Semenov, M., and Thomas, B., 2008. Vulnerability of horticultural crop production to extreme weather events. Aspects of Applied Biology, 88, 3-14.

Curtis, K. R., Yeager, I., Black, B., Drost, D., and Ward, R. 2014. Market and pricing potential for extended season fresh produce sales: An Intermountain West example. Journal of Food Distribution Research, 45(2).

Demchak, K. (2009). Small fruit production in high tunnels. HortTechnology, 19(1), 44-49.

Federal Crop Insurance Corporation, 2010. Report to Congress: Specialty Crop Report. FCIC, USDA. Available at: http://www.rma.usda.gov/pubs/2010/specialtycrop.pdf (Accessed January 2015)

Fleege, T. A., Richards, T. J., Manfredo, M. R., and Sanders, D. R., 2004. The performance of weather derivatives in managing risks of specialty crops. In NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, Missouri.

Grant, J.A., Caprile, J.L., Coates, W.C., Anderson, K.K., Klonsky, K.M., and De Moura, R.L. 2011. Sample Costs to Establish an Orchard and Produce Sweet Cherries. University of California Cooperative Extension. CH-VN-11. San Joaquin Valley, CA.

Heimfarth, L.E., and Musshoff, O., 2011. Weather index-based insurances for farmers in the North China Plain: An analysis of risk reduction potential and basis risk. Agricultural Finance Review, 71(2), 218-239.

Lang, G. A. 2013. Tree fruit production in high tunnels: current status and case study of sweet cherries. ISHS Acta Hort. 987: International Symposium on High Tunnel Horticultural Crop Production.

Lang, G. A. 2009. High tunnel tree fruit production: The final frontier? HortTechnology, 19(1), 50-55.

Lindsey, J. K., Duffy, P. A., Nelson, R. G., Ebel, R. C., and Dozier, W. A. 2009. Evaluation of risk management methods for satsuma mandarin. In 2009 Annual Meeting, January 31-February 3, 2009, Atlanta, Georgia (No. 46754). Southern Agricultural Economics Association.

Maughan, T. L., Curtis, K. R., Black, B. L., and Drost, D. T. 2015. Economic Evaluation of Implementing Strawberry Season Extension Production Technologies in the US Intermountain West. HortScience, 50(3), 395-401.

Miranda, C., Santesteban, L. G., and Royo, J. B. 2005. Variability in the relationship between frost temperature and injury level for some cultivated Prunus species. HortScience, 40(2), 357-361.

Moschini, G., and Hennessy, D. A. 2001. Uncertainty, risk aversion, and risk management for agricultural producers. Handbook of Agricultural Economics, 1, 88-153.

Murray, M., 2011. Critical Temperatures for Frost Damage on Fruit Trees. Utah pest fact sheet. IPM-012-11. Utah State University Extension. Available at: http://extension.usu.edu/files/publications/factsheet/pub__5191779.pdf (Accessed December 2014)

Musshoff, O., Odening, M., and Xu, W. 2011. Management of climate risks in agriculture–will weather derivatives permeate?. Applied Economics, 43(9), 1067-1077.

National Agricultural Statistics Service. 2015. Noncitrus Fruits and Nuts, 1984-2014. NASS, USDA, Washington, DC. Available at: http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1113 (Accessed February 2015)

National Agricultural Statistics Service. 2014. Citrus Fruits 2014 Summary. NASS, USDA, Washington, DC. Available at: http://usda.mannlib.cornell.edu/usda/current/CitrFrui/CitrFrui-09-18-2014.pdf (Accessed March 2015)

National Agricultural Statistics Service. 2006. Fruits and Tree Nuts: Blooming, Harvesting, and Marketing Dates. Agriculture Handbook Number 729. NASS, USDA. Washington, DC.

National Climatic Data Center: Climatological Data Publication. 2014. NCDC, NOAA Satellite and Information Service. Available at: http://www.ncdc.noaa.gov/IPS/cd/cd.html (Accessed December 2014)

Natural Resources Conservation Service. 2011. USDA Provides Update on Seasonal High Tunnel Pilot. NRCS, USDA. Available at: http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/newsroom/?cid=STELPRDB1040764 (Accessed January 2015).

Price, T. J., and Wetzstein, M. E. 1999. Irreversible investment decisions in perennial crops with yield and price uncertainty. Journal of Agricultural and Resource Economics, 24(1), 173-185.

Richards, T. J., and Manfredo, M. R. 2003. Infrequent shocks and rating revenue insurance: a contingent claims approach. Journal of Agricultural and Resource Economics, 28(2), 233-251.

Risk Management Agency. 2015. Actual Revenue History Sweet Cherry Pilot, Michigan, 2015. RMA, USDA. Available at: http://www.rma.usda.gov/fields/il_rso/2015/misweetcherriesarh.pdf (Accessed March 2015).

Risk Management Agency. 2014. Summary of Business Reports and Data: National Summary by Crops/States, 2014. RMA, USDA. Available at: http://www3.rma.usda.gov/apps/sob/current_week/cropst2014.pdf (Accessed March 2015)

Risk Management Agency. 2013. The Risk Management Safety Net: Portfolio Analysis-Market Penetration and Potential. RMA, USDA. Available at: http://www.rma.usda.gov/pubs/2013/portfolio/portfolio.pdf (Accessed October 2016).

Robinson, T. L., and Dominguez, L. I. 2013. Production of Sweet Cherries under High Tunnels in Either the Modified Spanish Bush and the Tall Spindle Systems. New York Fruit Quarterly. 21(2), 25–28.

Simon, G. 2006. Review on rain induced fruit cracking of sweet cherries (Prunus avium L.), its causes and the possibilities of prevention. International Journal of Horticultural Science, 12(3), 27-35.

Skees, J., Gober, S., Varangis, P., Lester, R., and Kalavakonda, V. 2001. Developing rainfall-based index insurance in Morocco, Policy Research Working Paper No. 2577, The World Bank, Washington, DC.

Song, F., Zhao, J., and Swinton, S. M. 2011. Switching to perennial energy crops under uncertainty and costly reversibility. American Journal of Agricultural Economics, 93(3), 768-783.

Turvey, C. G., Weersink, A., and Chiang, S. H. C., 2006. Pricing weather insurance with a random strike price: the Ontario ice-wine harvest. American Journal of Agricultural Economics, 88(3), 696-709.

Turvey C.G., Woodward, J., and Liu, E., 2014. Financial engineering for the farm problem. Agricultural Finance Review, 74(2), 271–286.

Turvey, C. G. 2001. Weather derivatives for specific event risks in agriculture. Review of Agricultural Economics, 23(2), 333-351.

U.S. Department of Agriculture, NASS. 2014a. Highlights: Farmers Marketing. 2012 Census of Agriculture. Available at: http://www.agcensus.usda.gov/Publications/2012/Online_Resources/Highlights/Farmers_Marketing/Highlights_Farmers_Marketing.pdf (Accessed January 2015)

U.S. Department of Agriculture, NASS. 2014b. 2012 Census of Agriculture. County Level Data: Fruits and Nuts, Michigan and New York. Available at: http://www.agcensus.usda.gov/Publications/2012/Full_Report/Volume_1,_Chapter_2_County_Level/ (Accessed January 2015)

Vedenov, D. V., and Barnett, B. J. 2004. Efficiency of weather derivatives as primary crop insurance instruments. Journal of Agricultural and Resource Economics, 29(3), 387-403.

Washington State University, 2009. Cost Estimates of Establishing and Producing Sweet Cherries in Washington. Extension Fact Sheet. FS022E.

Waterer, D., 2003. Yields and economics of high tunnels for production of warm-season vegetable crops. HortTechnology, 13(2), 339-343.

West, T., Sullivan, R., Seavert, C., and Long, L. 2012. Orchard Economics: The Costs and Returns of Establishing and Producing High-Density Sweet Cherries in Wasco County. Oregon State University, Extension Service. AEB 0032.

Wien, H. C., and Pritts, M. P. 2008. Use of high tunnels in the Northeastern USA: Adaptation to cold climates. In International Symposium on Strategies Towards Sustainability of Protected Cultivation in Mild Winter Climate 807. pp. 55-60.

# OTHER A.E.M. WORKING PAPERS

| WP No | Title | Fee (if applicable) | Author(s) |
|---|---|---|---|
| 2016-15 | The Economic Impacts of Climate Change on Agriculture: Accounting for Time-invariant Unobservables in the Hedonic Approach | | Ortiz-Bobea, A. |
| 2016-14 | Demystifying RINs: A Partial Equilibrium Model of U.S. Biofuels Markets | | Korting, C., Just, D. |
| 2016-13 | Rural Wealth Creation Impacts of Urban-based Local Food System Initiatives: A Delphi Method Examination of the Impacts on Intellectual Capital | | Jablonski, B., Schmit, T., Minner, J., Kay, D. |
| 2016-12 | Parents, Children, and Luck: Equality of Opportunity and Equality of Outcome | | Kanbur, R. |
| 2016-11 | Intra-Household Inequality and Overall Inequality | | Kanbur, R. |
| 2016-10 | Anticipatory Signals of Changes in Corn Demand | | Verteramo Chiu, L., Tomek, W. |
| 2016-09 | Capital Flows, Beliefs, and Capital Controls | | Rarytska, O., Tsyrennikov, V. |
| 2016-08 | Using Unobtrusive Sensors to Measure and Minimize Hawthorne Effects: Evidence from Cookstoves | | Simons, A., Beltramo, T., Blalock, G. and Levine, D. |
| 2016-07 | Economics and Economic Policy | | Kanbur, R. |
| 2016-06 | W. Arthur Lewis and the Roots of Ghanaian Economic Policy | | Kanbur, R. |
| 2016-05 | Capability, Opportunity, Outcome - -and Equality | | Kanbur, R. |
| 2016-04 | Assessment of New York's Pollution Discharge Elimination Permits for CAFO's: A Regional Analysis | | Enahoro, D., Schmit T. and R. Boisvert |
| 2016-03 | Enforcement Matters: The Effective Regulation of Labor | | Ronconi, L. and Kanbur, R. |
| 2016-02 | Of Consequentialism, its Critics, and the Critics of its Critics | | Kanbur. R |

Paper copies are being replaced by electronic Portable Document Files (PDFs). To request PDFs of AEM publications, write to (be sure to include your e-mail address): Publications, Department of Applied Economics and Management, Warren Hall, Cornell University, Ithaca, NY 14853-7801. If a fee is indicated, please include a check or money order made payable to Cornell University for the amount of your purchase. Visit our Web site (*http://dyson.cornell.edu/research/wp.php)* for a more complete list of recent bulletins.