

ARTICLE

Potential use of weather derivatives in hedging aggregate viticulture yields: An analysis of the Niagara region of Canada

Don Cyr¹, Joseph Kushner² and Mingtian Zhang³

¹Goodman School of Business, Brock University, St. Catharines, ON, Canada, ²Department of Economics, Brock University, St. Catharines, ON, Canada and ³OEVI Program, Brock University, St. Catharines, ON, Canada

Corresponding author: Don Cyr, email: dcyr@brocku.ca

Abstract

Although potentially useful for financially hedging systemic weather-related risks, weather contracts/derivatives (also referred to as parametric insurance) have not seen wide adoption in agriculture outside of applications in developing countries, frequently supported by governments and non-governmental organizations (NGOs). A significant impediment is the lack of financial firms willing to stand ready to sell weather derivatives to individual agricultural producers in the over-the-counter market who, due to the localized nature of weather, face idiosyncratic weather-related risks. In particular, the administrative and reinsurance costs of supplying relatively small contracts with specific terms to many different producers are often prohibitive. The current study considers the potential use of weather derivatives in hedging the aggregate yield/revenues of viticulture producers represented by an industry association located in the province of Ontario, Canada. We examine the sensitivity of aggregate industry yields to several relevant weather-related risks employing copula function analysis. We then consider the potential of a weather derivative in hedging the financial risk associated with cold winter temperatures, which pose the greatest risk to aggregate vinifera yields. The issue of attributing costs and payouts to individual association members remains unresolved, and several alternatives are suggested.

Keywords: hedging; parametric insurance; viticulture; weather contracts

JEL classifications: G22; G32; L66; Q14

1. Introduction

Weather and climate are, as in any agriculture sector, significant risk factors that affect viticulture yield and quality. Although various methods are employed to mitigate the financial risks of weather, the use of financial contracts known as weather derivatives has not seen extensive uptake, particularly with respect to agriculture in developed countries. This is the case despite their potential for mitigating systematic

© The Author(s), 2023. Published by Cambridge University Press on behalf of American Association of Wine Economists. This is an Open Access article, distributed under the terms of the Creative Commons Attribution licence (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted re-use, distribution and reproduction, provided the original article is properly cited.

weather risk as opposed to catastrophic risk for which weather risk insurance is more frequently employed. Systemic weather risk refers to suboptimal weather conditions that may result in reduced yields or quality of the agricultural commodity and consequently lower producer revenues. As compared to weather insurance, which involves the costly administrative processes of proof of loss and insurance adjustment, payments associated with weather contracts are automatically triggered by an event exceeding a predefined parametric (bioclimatic or weather measurement) threshold. The payment structure can be simply set to varying predefined conditions, again replacing reimbursement based on actual losses suffered. An additional appeal to the purchaser of the weather contract is the absence of deductibles and exclusions typically associated with insurance.

In terms of agriculture, payouts from weather derivatives are simply based on the observations of a weather-related bioclimatic index over a period such as a growing season, typically measured at an independent government-operated weather station. Contracts are generally similar to financial put or call options on stocks, with the weather index as the underlying asset. Their payout complexity can be increased with caps, collars, and other structures, similar to financial derivatives, in order to suit the contract purchaser.

Although significant interest and use in terms of agriculture have been seen in the developing world, particularly for subsistence farming, these applications have frequently been supported by government or non-government agencies. Carter *et al.* (2014) provide a growing list of countries in the developing world in which various programs have been implemented, largely for subsistence farming, and supported by organizations such as the World Bank and government insurance agencies, in collaboration with reinsurers such as MicroEnsure, Munich Re, and Swiss Re. Although the Chicago Mercantile Exchange launched standardized weather contracts in 1999, their use is primarily in the energy market, with little application to agriculture. Non-standardized contracts traded in the over-the-counter market have seen very little uptake, particularly in agriculture (Roussis *et al.*, 2017). Similarly, despite a number of studies modeling potential viticulture applications (Turvey, Weersink, and Chiang, 2006; Cyr and Kusy, 2007; Cyr, Kusy, and Shaw, 2008, 2010; Zara, 2010; Yandell, 2012; Cortina and Sánchez, 2013), actual applications are rare at best. This lack of application stems partly from issues in terms of both demand and supply.

A. Demand side constraints

The lack of application stems partly from the idiosyncratic basis risk that individual producers face. Basis risk can arise primarily due to spatial distances from weather measuring stations on the part of the producer, resulting in the weather index underlying the contract not correlating well with the yield or quality of the harvest variable. As a result, individual producers may require relatively small contracts with idiosyncratic contract conditions. Consequently, there have been extensive studies on the willingness-to-pay on the part of potential purchasers of such contracts. Almost without exception (Edwards and Simmons, 2004; Simmons, Edwards, and Byrnes, 2007), however, these studies have primarily focused on agricultural producers in the developing world (Budhathoki *et al.*, 2019; Fonta *et al.*, 2018; Fahad and Jing, 2018; Kong

et al., 2011; Turvey and Kong, 2010; among others), partially due to the lack of extensive applications in developed countries. An interesting sub area of this literature is with respect to factors that affect willingness-to-pay (Liu et al., 2019; Wairimu, Obare, and Odendo, 2016; Akter et al., 2016; Lin et al., 2015; Abebe and Bogale, 2014; among others). In addition to basis risk, these studies have found that factors affecting levels of risk aversion, such as income and prior familiarity with weather derivatives, also influence willingness-to-pay. More recently, prior experience with extreme weather events has been found to contribute positively to willingness-to-pay for weather derivatives (Liu et al., 2019; Senapati, 2020). Hence, increased volatility and occurrence of extreme weather events associated with climate change can have a significant impact on viticulture (Jones et al., 2022; Ashenfelter and Storchmann, 2016; Van Leeuwen and Darriet, 2016), and the growing awareness on the part of producers (Demberger, 2017; Mercer, 2018) may ultimately contribute to a greater usage of weather contracts.

B. Supply side constraints

The issue of basis or spatial risk on the part of individual producers can also result in a lack of interest on the part of financial institutions/insurers in supplying weather derivatives in the over-the-counter market due to the relatively small size of the contracts. The result is increased bureaucracy and administrative costs on the part of the supplier (Salgueiro, 2019). Although the costs associated with claim investigations are not necessary with weather derivatives, regulatory compliance in the insurance industry may still require the need to collect evidence that the claimholder has an insurable interest (Lin and Kwon, 2020). This requirement differentiates the use of weather contracts as an insurance-related tool as opposed to a speculative investment. Such contracts may also require clauses to cover potential incidents where calculative market devices employed in the weather measuring station fail (Johnson, 2021). A variety of other inhibitors in terms of the insurance/reinsurance markets can exist related to actuarial processes and the complexity of the non-stationarity of weather (Odening and Shen, 2014). Individual producer basis risk can also be of concern from a reputational perspective on the part of the insurer. Dissatisfaction with the correlation between payouts and losses on the part of the individual producers can result in reputational damage for the insurer and potentially affect the sale of other insurance products (Lin and Kwon, 2020). An additional issue is systemic risk, which results in many claims/payouts simultaneously. This can be mitigated somewhat by broadening the trading area or through aggregation of contracts (Salgueiro and Tarrazon-Rodon, 2021).

A potential solution is for the aggregation of the production to be hedged among similar producers, with subsequent costs and payouts to be distributed among participating members based on an agreed-upon formula within the group. This results in a single, more substantial contract, the supply of which may be of interest to major financial institutions. In addition, employing a producer association may contribute significantly to the understanding and acceptance of weather contracts (Zara, 2010). This concept of aggregation is not new and has been suggested previously (Woodward and Garcia, 2008).

Consequently, the purpose of this study is to examine the potential for hedging a major weather-related risk for aggregate producers in a localized area employing weather derivatives. To this end, we explore this potential with respect to an association of grape growers largely located in the Niagara region of Canada. The Niagara region is a relatively small geographic, cool-climate viticulture region in Canada, where the majority of the province of Ontario's wine grapes are grown and harvested. The Grape Growers of Ontario essentially serves as a marketing board for the majority of the region's grape growers. Employing copula function analysis, we explore the sensitivity of aggregate grape yields of the association to various weather variables representing the major risks to viticulture in the region over the period of 2003–2018 and explore the potential use of a weather contract in hedging aggregate yield/revenue risk.

Section I provides an overview of the major grape-growing regions in the province of Ontario, with the Niagara region being by far the largest. The Grape Growers of Ontario and its function are also introduced. Section II describes the major weather-related risks that grape growers face and introduces appropriate bioclimatic indices created to represent these risks. Section III provides an analysis of the sensitivity of aggregate yields to the various bioclimatic indices employing copula function analysis. Section IV provides a simulation of how a specifically designed weather derivative contract could be employed to hedge aggregate revenues with respect to cold winter temperatures. Section V concludes.

II. Ontario grape and weather environment

The Ontario wine region, like most other wine regions in North America, has in recent years transformed itself into a producer of world-class wines. In doing so, it has experienced phenomenal growth (Bramble *et al.*, 2007). Not surprisingly, given its location, the region is characterized by cool-climate viticulture. Although the summers are warm, the growing season is short, with the potential for spring frosts and wet fall harvests. Winters can be extremely cold and, in recent years, have suffer from frequent occurrences of polar vortexes. Although such cold temperatures are welcomed by the producers of icewines, they can result in damage to the vines and consequent loss of production. Vineyard management practices such as burying the vines and the use of wind machines to circulate air flow can lessen spring frost and winter damage; however, yields can still be significantly reduced.

Ontario is the largest producer of grapes in Canada, accounting for approximately 80% of Canadian production. Ontario's viticulture industry, which consists of three primary areas—the Niagara Peninsula, Lake Erie, and Pelee Island—is situated between 41° and 44° North, which is the same latitude shared by Burgundy and many cool climate wine regions of Europe. Figure 1 provides a diagram of the three producing areas and the location of a primary government-operated weather measuring site, the Vineland weather station.

The Niagara Peninsula's 14,000 acres of grape production is the largest of the three areas, accounting for 93% of Ontario's production and the greatest of all regions in Canada (VQA, 2019). The cultivation of grapes is made possible by the moderating effect of two adjacent Great Lakes, Lake Ontario and Lake Erie, which have cool

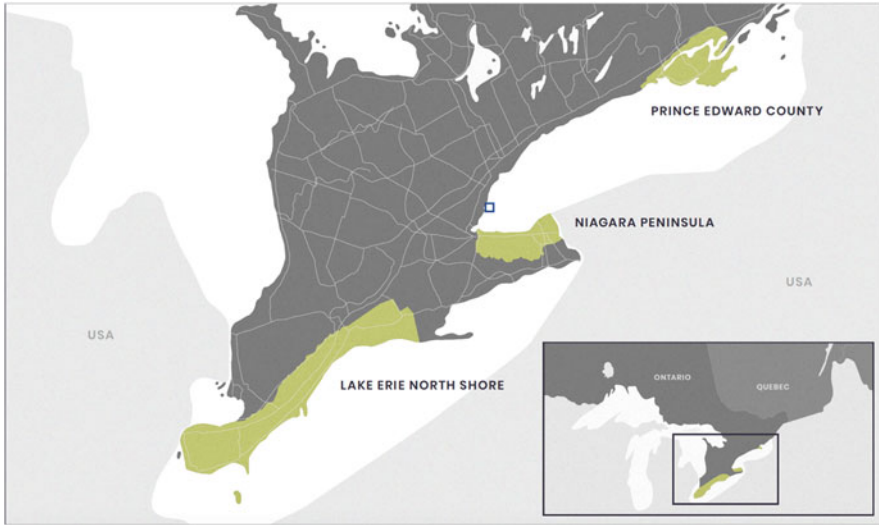


Figure 1. Primary Ontario wine grape producing areas and Vineland weather station.

Notes: The three primary viticulture regions in Ontario consist of Prince Edward County, Niagara Peninsula, and Lake Erie North Shore. The location of the Vineland weather station is indicated as a white square in the Niagara Peninsula region.

Source: Ontario Wine Appellation Authority (VQA.ca).

summer temperatures and warm winter temperatures and extend the growing season in the fall. Typical cool climate varieties such as Riesling, Cabernet Sauvignon, and Pinot Gris are common with Chardonnay, Riesling, Cabernet Franc, and Merlot being the top four planted vinifera varieties. Hybrid varieties such as Vidal and Baco Noir are also widely planted for icewine as well as table wine production. The Vintners Quality Alliance (VQA) is an appellation system that carries out testing and monitoring to regulate VQA wine quality and origin.

The majority of the financial risks to Ontario grape growers are weather-related: extremely cold temperatures in winter can kill or significantly damage grapevines; spring or winter frost affects bud formation, which leads to yield deduction; and icewine producers face a limited harvest window of optimal weather conditions. More recently, economic loss can also be caused by increasing weather volatility due to climate change (Ashenfelter and Storchmann, 2016). Indeed, the number of days, precipitation, and occurrence of extreme maximum temperatures ($\geq 30^{\circ}\text{C}$) have significantly increased in the past 35 years (Shaw, 2017). Although rising temperatures and precipitation extended the growing season, they can be accompanied by fungal diseases and drainage problems (Adelsheim et al., 2016).

To manage the weather risks in Ontario, three options are typically considered: traditional viticulture practices, new technological developments, and crop insurance. Traditional viticulture practices such as suckering, modified training systems, and canopy management strategies are commonly used but are labor intensive and ineffective in extreme weather events (Seccia, Santeramo, and Nardone, 2016). Recent technological developments involve better weather prediction systems and innovations such as

advanced irrigation systems and the use of wind machines to mitigate the impact of frost or extreme cold temperatures in the winter. Although effective, high capital costs are required. For extreme catastrophic weather events, grape growers can purchase crop insurance from AGRICORP, a province of Ontario crown corporation that covers yield reduction (AGRICORP, 2022). The coverage is based on the yield history and correlated only to extreme weather events such as drought, excessive wind causing structural damage, flood, hail, ice damage, lightning, and winter freeze injury (Salgueiro, 2019). However, proof of damage is required and difficult to evaluate as the yield loss caused by annual weather volatility and climate change is not covered.¹

Weather derivatives, where the payout is based on the levels of an observable weather index, without the need for proof of damage, are well designed for systemic weather risk. Financial payouts are triggered if an observed weather index diverts sufficiently from an agreed-value specified in the derivative contract. The measurement of the weather variable is typically done at an agreed-upon independent government-run metrological site. In Canada, such sites are operated throughout the country by a government agency called Environment Canada.

The agriculture industry has lagged in the use of weather derivatives, but now, because of concerns with climate change, they may be of increasing interest on the part of producers (McCarthy, 2003; Turvey and Kong, 2010; Ali, 2013). Increased weather volatility, accompanied by increasing growing days, is becoming commonplace throughout the world, including the Niagara region (Adelsheim *et al.*, 2016; Shaw, 2017). Warming can lead to problems such as sunburn, water deficit, and cluster loss, contributing to reduced crop yields. Also, the wine quality could be affected by decreasing metabolites such as acids and aromatic compounds at a hot temperature. Crop insurance is not well suited for covering these losses. For example, the crop insurance offered by AGRICORP only pays out to individual grape growers when their yield falls below an agreed yield percentage of a five-year moving average. The cost to participating grape growers in Ontario in terms of crop insurance through AGRICORP involved average annual premiums of \$4,867,000 over the five year period of 2014–2018. Premiums exceeded approved claims by an average of \$2,146,800 per year, or a net cost of approximately \$8,900 per annum for the participating growers.

In contrast, as previously noted, weather derivatives only hedge against negative weather-related measurements rather than specific crop yield, or the actual physical loss (Alexandridis and Zaprani, 2013). Weather derivative payouts do not require proof of yield damage. The advantage is that in such cases, the grower will try to obtain the highest yield instead of possibly reducing the effort in a negative weather condition in order to facilitate proof of damage in the case of insurance, an issue known as moral hazard.

¹For a case study of the Ontario grape and wine industry's adaptation to climate change, see K. Pickering *et al.* (2012), who describe the transdisciplinary approach of the Ontario Grape and Wine Research Network as well as some preliminary results to highlight the opportunities for innovation and improving existing strategies to adapt to climate change.

A. Grape growers of Ontario and aggregate yields

Originally formed as the Grape Growers of Ontario Marketing Board in 1947, the Grape Growers of Ontario (GGO) is an industry association that represents approximately 480 grape growers in the province of Ontario, with over 17,000 acres of vineyards and approximately 98% of grape production destined to processors for winemaking. The remaining 1–2% are employed for jams, juice, or home wine making. Wine grape production is typically comprised of 37% hybrids and 62% vinifera by tonnage. The primary function of the GGO, in addition to research and government lobbying, is to represent the interest of grape growers in dealing with processors. Although grape growers contract their grape sales directly with processors, the GGO negotiates minimum prices for all grapes sold to processors. Prices per tonne are negotiated annually and are categorized by grape varietal (vinifera and hybrids) along with subcategories, as well as brix levels (Grape Growers of Ontario, 2019). On average, 80% of the wine grape producers are located on the Niagara peninsula, representing over 90% of the wine grape acreage and production in Ontario.

Since 2003, the GGO has reported annually on total grape tonnage sold as well as tonnage of hybrids and vinifera on the part of its members. Figures 2 through 4 show the annual aggregate yields in terms of vinifera and hybrid varieties and the total yields, respectively, for the years 2003–2018.

Figures 2, 3, and 4 all indicate a statistically significant increasing trend in terms of annual yields, although total acreage has remained relatively constant over the period. The significant upward trend is due to improvements in viticulture practices and the maturity of the vines. Hence, in Section III, when relating weather variables to yield over the time period, we will employ detrended yield data in order to isolate the effects of various weather events.

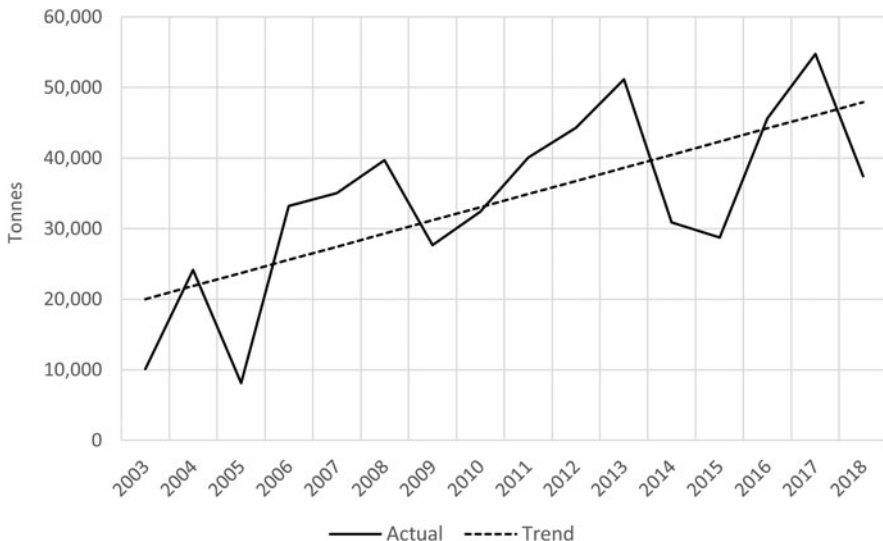


Figure 2. Grape growers of Ontario aggregate vinifera yield (2003–2018).

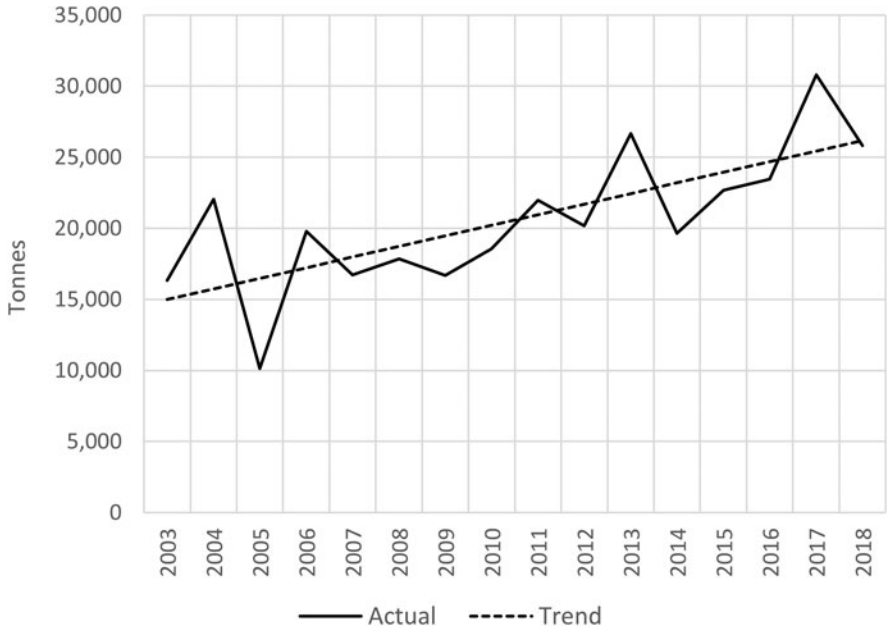


Figure 3. Grape growers of Ontario aggregate hybrid yield (2003–2018).

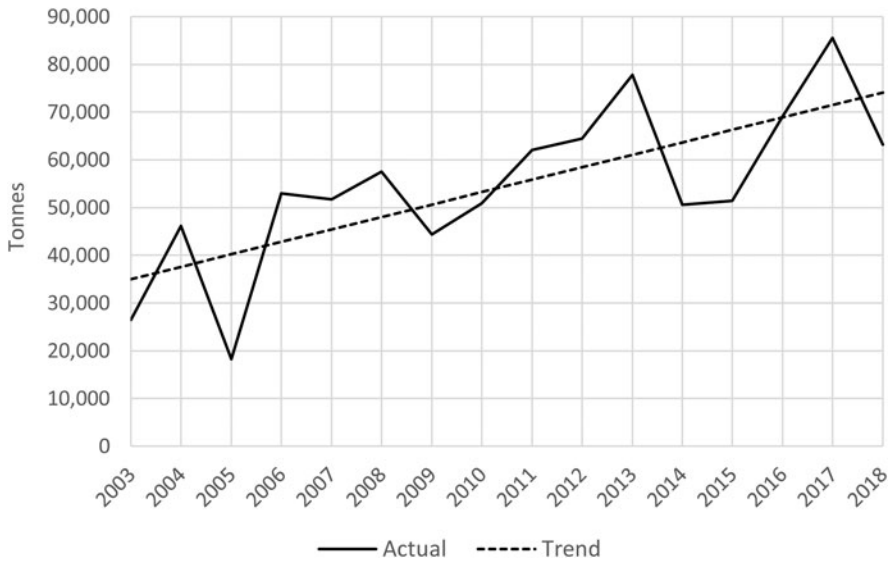


Figure 4. Grape growers of Ontario aggregate yield (vinifera and hybrid) (2003–2018).

III. Weather variables of interest

We begin by constructing primary weather indices of potential interest employing 2000–2018 daily weather data from Environment Canada’s Vineland weather station in the Niagara Peninsula, whose location is indicated in [Figure 1](#). It is the standard weather station employed for agriculture in the Niagara region. The data used includes daily maximum temperature, minimum temperature, average temperature, and precipitation. Although such weather data is available as far back as 1965, Cyr and Kushner (2022) find significant abrupt structural changes (“tipping points”) in weather in the Niagara Peninsula over the period of the 1990s believed to be due to climate change. A stable period of albeit higher volatility in weather risk factors is observed, but with no statistically significant trend from 2000 onward.

A. Growing season bioclimatic indices—Winkler and Huglin

Bioclimatic indices have long been used to characterize grape growing regions. In terms of the growing season, we explore the sensitivity of aggregate yields to both the Winkler (1962) and Huglin (1978) indices. The Winkler index is based upon growing degree days and subdivides grape-growing districts into five climatic zones. Ontario is characterized as Region 2, representing 1371–1648°C annual heat units or degrees. The Huglin index incorporates the number of sunshine hours through a latitude index.

The Winkler index (WI) is calculated as:

$$WI = \sum_{April\ 1}^{Oct\ 30} (T_{AVG} - 10^{\circ}C), \quad (1)$$

where T_{AVG} is the daily average temperature average from April 1 to September 30; 10°C is subtracted from T_{AVG} as grape vines do not typically grow below 10°C.

The Huglin index (HI) is calculated as:

$$HI = \sum_{April\ 1}^{Sept\ 30} ((T_{AVG} - 10^{\circ}C) + (T_{MAX} - 10^{\circ}C)/2)k, \quad (2)$$

where T_{MAX} indicates the daily maximum temperature. The constant k denotes a parameter dependent on the latitude of the location. In this case, Ontario is located at 41° to 44° North, and the value of 1.03 is employed. [Figure 5](#) provides a graph of the annual calculation of the Winkler and Huglin indices over the period of 2000 through 2018.

B. Winter injury

Due to the potential effect of cold winter weather in cool climates such as Ontario, several variations of a bioclimatic winter injury index based on minimum daily temperatures over the winter months (November through March) were chosen to explore the relationship with yield. Lower temperatures can lead to changes in the hormone

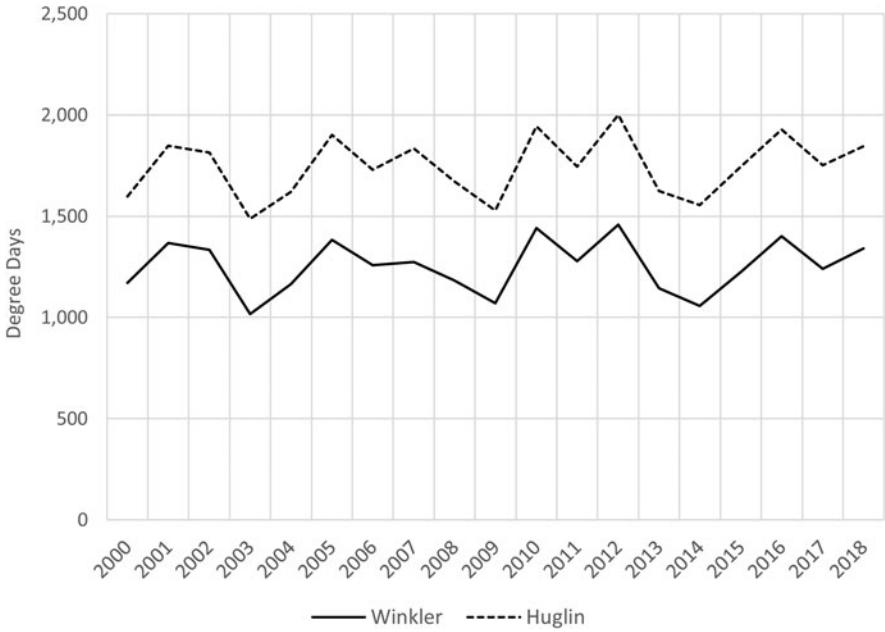


Figure 5. Winkler and Huglin indices (2000–2018).

levels of grapevines, and not every tissue acclimates to the same degree. Therefore, different temperature references were used to assess the yield/index relationship. The *Winter Injury* measure was calculated as:

$$Winter\ Injury = \sum_{Nov\ 1}^{Mar\ 31} [T_{min}] - S; \text{ if } [T_{min}] - S \leq 0, \text{ equal } 0 \quad (3)$$

where T_{min} denotes daily minimum temperatures in the months of November through March of January, while S indicates the reference temperatures of -5 , -10 and -15°C , which are subtracted from the absolute value of T_{min} . Thus, the variable measures the cumulative number of degrees (degree days) the daily minimum temperatures were below the reference temperature over the winter period. Figure 6 provides a graph of the annual *Winter Injury* variable for all three calculations of $S = -5$, -10 , and -15°C .

C. Harvest rainfall

Heavy rainfall during the prime ripening and harvest period of September through October can have a significant detrimental effect on the ultimate yield and quality of the grapes and, consequently, the value of the harvest. In particular, the uptake of water by the grapes can result in juice dilution and lower Brix levels, as well as splitting of the grapes. Excessive rainfall can also induce growers to harvest the crop early, resulting in a less ripened crop and hence a lower value (Shaw, 2017).

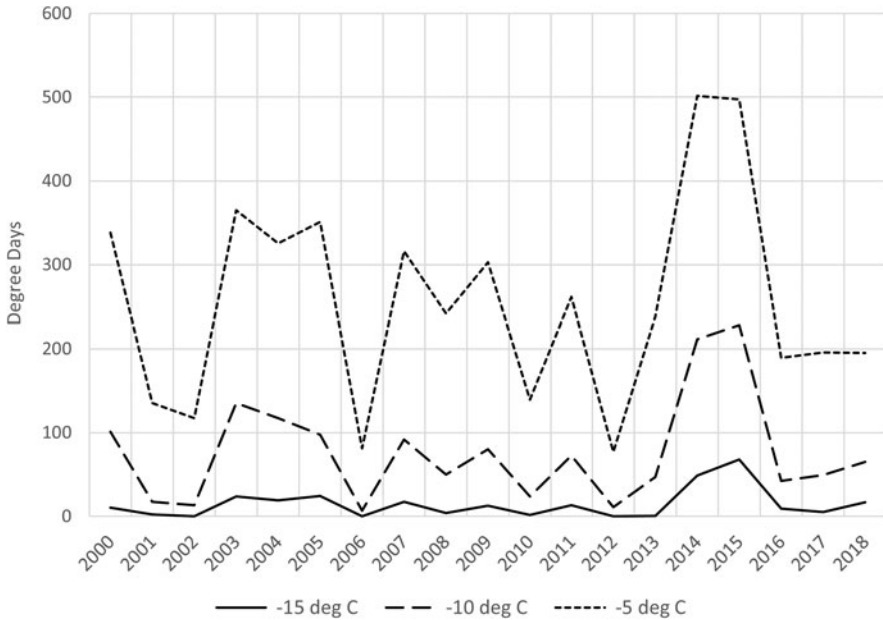


Figure 6. Time series of winter injury (2000 to 2018): Degree days below -15 , -10 and -5°C .

The measure of harvest rainfall consists of the cumulative daily rainfall (mm) over the months of October through September, calculated as:

$$\text{Harvest Rainfall} = \sum_{\text{Sept } 1}^{\text{Oct } 31} \text{daily Rainfall} \quad (4)$$

Figure 7 provides a diagram of the Harvest Rainfall variable over the period of 2000–2018.

IV. Data analysis

A. Copula function analysis

Linear models were commonly used to design weather contracts, but more recently, non-linear modeling has been employed (Salgueiro, 2019; Bokusheva, 2011; Goodwin and Hungerford, 2015). For example, Bokusheva (2018) used a non-linear copula function based on both a Ped Drought Index and Cumulative Rainfall Index, showing improved results compared to a linear model. Consequently, copula function modeling is first employed to determine which of the bioclimatic indices listed in Section II is of greatest risk to aggregate yields. An option price is then constructed based on a Monte Carlo simulation employing the best-fitting copula function for the weather index exhibiting the greatest risk to harvest yields. Such an approach to an option price, as opposed to a Black-Scholes-type option pricing model, is due to the lack

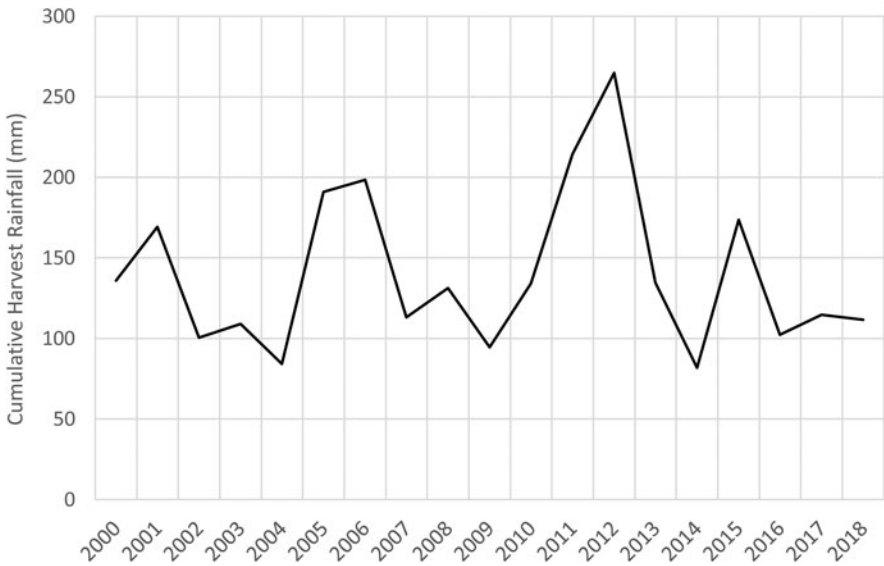


Figure 7. Cumulative (September through October) harvest rainfall in mm: 2000 to 2018.

of market liquidity and completeness. In general, the market for weather derivatives is relatively small and illiquid, meaning that there may be limited trading activity and price discovery.

According to Sklar's (1973) theory, any m -dimensional distribution function can be described in terms of two elements: marginal distributions and dependence structure. Copula functions allow marginal distributions of variables to combine to form a joint distribution (Trivedi and Zimmer, 2005). Copula functions identify the dependence structure between variables without sacrificing the attractive properties of the marginals (Trivedi and Zimmer, 2005). For example, for an m -variate function F , the copula associated with F is a distribution function:

$$C: [0, 1]^m \rightarrow [0, 1] \text{ that satisfies } F(y_1, \dots, y_m) = C(F_1(y_1), \dots, F_m(y_m); \theta), \quad (5)$$

where θ is a vector of parameters referred to as the dependence parameters, measuring the dependence between the marginal distributions. In bivariate applications, θ is typically a scalar (Trivedi and Zimmer, 2005).

There are two distinct categories of copula functions: parametric and non-parametric. The parametric can be used to capture the dependence structure of variates with known parameters. In this study, we examine elliptical and Archimedean parametric copula functions. The Archimedean family of copula functions includes Clayton, Frank, and Gumbel. Each has a closed form and a single parameter to control the degree of dependence, which enables them to capture any asymmetric non-linear tail dependence structures between covariates. Elliptical copulas such as the Gaussian or Normal and Student- t copulas do not have a closed form but are readily extendable to multivariate applications. They are, however, restricted to radial

symmetry, which limits their ability to fully capture asymmetric tail dependence structures.

Goodness-of-fit testing for copula functions remains a complex and relatively unresolved area (Hasebe, 2013). The power of testing methods depends on sample size, dimensionality, and the function being tested. Although there is no agreement on methodology, a common approach to bivariate copula selection is to use maximum likelihood goodness-of-fit tests such as the Akaike information criterion (AIC). Hence, we identify the copula function that best models dependence by applying maximum likelihood goodness-of-fit tests, including AIC, Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQIC), for comparison.

Based on 16 years of detrended aggregate vinifera, hybrid, and total yield data (2003–2018), *Vose ModelRisk* software was employed to identify the best-fitting copula function for each weather index. *ModelRisk* is a risk modeling software often employed in industry and research for risk management applications. Research applications include not only finance (Habibi and Habibi, 2016; among others) but also engineering (Ahmed et al., 2021; Ryberg et al., 2019; among others) as well as agriculture-related endeavors (McPhee et al., 2016; Pasaribu et al., 2021; among others). Similar applications were employed (Cyr, Kwong, and Sun, 2017, 2019) in terms of the relationship between wine ratings and Bordeaux en primeur wine prices. Although more sophisticated analyses may be employed in all steps that follow, the use of the software and approach provides a benchmark for the value of a proposed weather derivative.

Consequently, the results in Table 1 show the best-fitting copula function identified for each of the three aggregate GGO yield measures and the various weather indices of interest. Other criteria, such as SIC and HQIC, were consistent with the AIC test statistic results and are available from the authors. The table also provides the resulting parameter coefficient, which, in the case of the Gaussian copula (the best-fitting copula in all cases), is the Spearman rank correlation coefficient (ρ).

Table 1. Best-fitting copula function and parameter coefficient for detrended yields and weather variables

Weather index	Vinifera yield	Hybrid yield	Total yield
Degree days -15	Gaussian -0.7395*	Gaussian -0.3305	Gaussian -0.6943
Degree days -10	Gaussian -0.6764	Gaussian -0.2236	Gaussian -0.6130
Degree days -5	Gaussian -0.6296	Gaussian -0.2742	Gaussian -0.5890
Winkler	Gaussian 0.0996	Gaussian -0.2713	Gaussian 0.0012
Huglin	Gaussian 0.0847	Gaussian -0.3184	Gaussian -0.0247
Harvest rainfall	Gaussian 0.1547	Gaussian -0.1780	Gaussian 0.0733

Note: *The copula parameter coefficient in the case of the Gaussian Copula function is the Spearman rank correlation coefficient ρ .

As indicated in [Table 1](#), the Gaussian copula was found to be the best fitting function of the five copula functions tested (Gaussian, Student-t, Gumbel, Clayton, and Frank) in all cases. Although the Gaussian copula can capture symmetric tail dependence, it is interesting to note that no asymmetric tail dependence was identified. Such asymmetric tail dependence would occur when there are significantly higher correlations between yields and extreme values of the weather indices at one end of their spectrum and would be indicated by the best-fitting copula being variants of either the Clayton or Gumbel copula. For example, one might expect significantly higher tail dependence in terms of a greater negative correlation between high values of the winter injury variables and yields. This may be the case for individual producers; however, most likely due to the aggregation of the yield data across producers, the best-fitting copula function in all cases was that of the Gaussian. Although the Student-t copula can at times more effectively capture symmetric tail dependence (Lourme and Maurer, 2017), it was often the relatively least-fitting copula in the applications. The results of Lourme and Maurer were in relation to international financial market indices and may be relevant in that case due to the increased correlation of financial markets during and after the 2008 financial crisis.

Also noteworthy were the relatively low correlation coefficient values in terms of yields and the Winkler, Huglin, and precipitation indices. Correlation between yields and the winter injury indices was of the highest value, particularly in terms of degree days -15°C , exhibiting a rank correlation of $\rho = -.7359$ with detrended vinifera yields. This greater sensitivity of vinifera yields is understandable, as hybrid grape varieties are more suited to cool climates. Given this significantly greater negative correlation, we focus our efforts on the effectiveness of a weather contract to hedge aggregate vinifera yields, with the underlying variable being the winter injury measure of -15°C degree days.

One variable of weather-related risk that was not included in the study was that of spring frost. Although a potential risk factor, cultivation practices as well as the use of wind technology have significantly reduced this risk for Ontario grape growers in recent years.

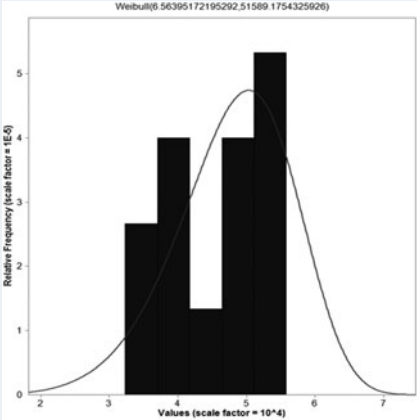
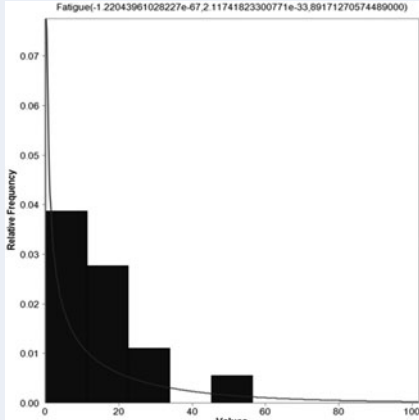
B. Marginal distributions identification

As noted, the benefit of copula function modeling is the ability to identify marginal distributions independently from the identification of the copula function that characterizes the nonlinear correlation between the variables, all together defining the joint probability distribution function. In the case of the detrended vinifera yield and winter injury measure of -15°C degree days, again the AIC, SIC, and HQIC test statistics were employed to identify the most representative marginal probability distribution functions. In total, 134 different possible probability distributions were considered and ranked with consistent results among the test statistics. A truncation constraint of non-negativity was employed in both cases. [Table 2](#) indicates the resulting marginal distributions identified.

The Weibull distribution can take many forms depending on its parameters and can also be used to model reliability or lifetime data.

The Fatigue Lifetime distribution (also known as the Birnbaum–Saunders distribution) is a probability distribution used extensively in reliability applications to model

Table 2. Best fitting marginal distribution for detrended vinifera yield and winter injury -15 degree days

	Vitis Vinifera	Degree Days -15
Distribution	Weibull	Fatigue
Distribution Parameters	6.56, 51589.18	-4.32e-43, 3.17e-21, 66025358775.71
Graphical representation of data and best fitting distributions		

failure times and hence often observed in insurance applications. Such decay-style probability distributions are logical given the nature of the winter injury index, which is characterized as number of days over which the temperature is below certain set points and hence highly skewed. The generalized three-parameter Birnbaum–Saunders distribution (α, β, γ) is a right-skewed distribution bounded at a minimum of α ; β is a scale parameter, while the parameter α controls its shape as reflected in skewness and kurtosis. With a value close to zero for α ($-4.32e-43$), this is consistent with the data for the -15 degree winter injury as it cannot take a negative value. The low value of β ($3.17e-21$) is reflective of the low spread of the distribution. The large value for the parameter γ provides the shape of the Birnbaum–Saunders distribution indicated in Table 2. The data displayed in Figure 6 indicates that its value is frequently close to or equal to zero, consistent with the extreme kurtosis and skewness of the distribution reflected in its γ value.

C. Monte Carlo simulation

Given the copula function and marginal distribution identification results, a Monte Carlo simulation of 5,000 iterations was performed, including the identified marginal distribution for vinifera yields (Weibull distribution) and winter injury -15°C degree days (Fatigue distribution) along with the identified Gaussian copula function ($\rho = -0.7395$). Figure 8 provides a plot of the histogram for the degree days -15°C ; Figure 9 provides the histogram for the simulation of vinifera yields; and Figure 10 provides the scatter plot of the simulation of the joint distribution.

D. Simulated weather derivatives contract for hedging vinifera yield

Given the analysis from earlier, it is possible to examine the potential for the GGO to employ a call option written on degree days -15°C to hedge the vinifera harvest yield value. Although the average price per tonne of vinifera grapes was not able to be

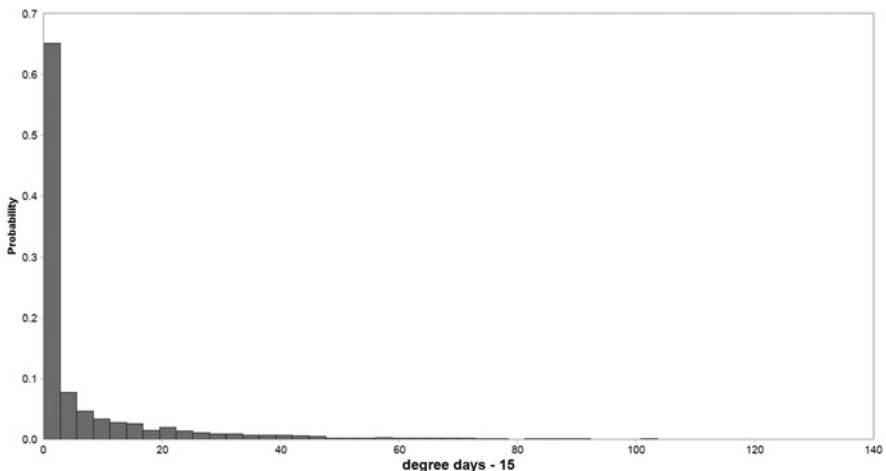


Figure 8. Simulation histogram of winter injury degree days -15°C .

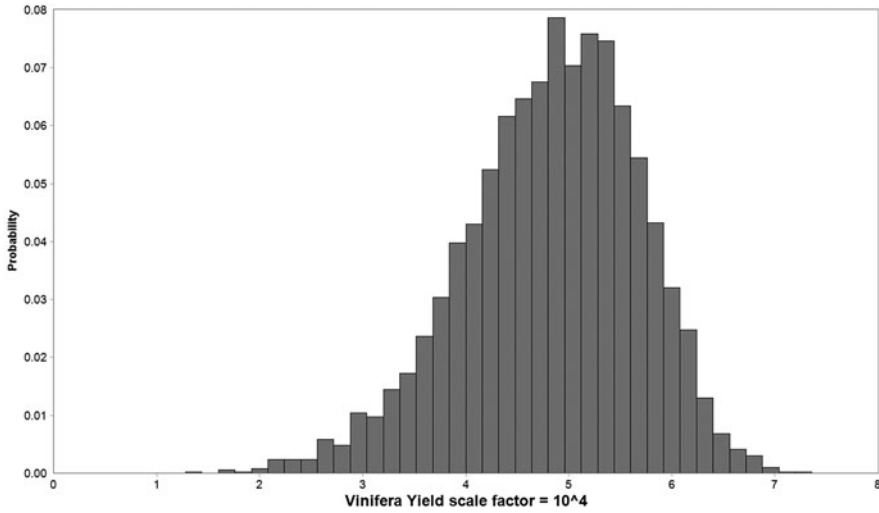


Figure 9. Histogram plot of simulation vinifera yields.

obtained, the 2019 GGO annual report indicates that the average price per tonne (all varietals) was \$1,345 in 2019. Employing the detrended yield data and assuming this price per tonne for purposes of a simulation, Table 3 provides values for the total vinifera yield along with the observed -15°C degree days over the 16-year period of data.

We will assume that one year from harvest, the GGO could potentially purchase a call option on degree days -15°C in order to hedge potential losses due to winter injury. The question arises as to what a reasonable strike price should be, along

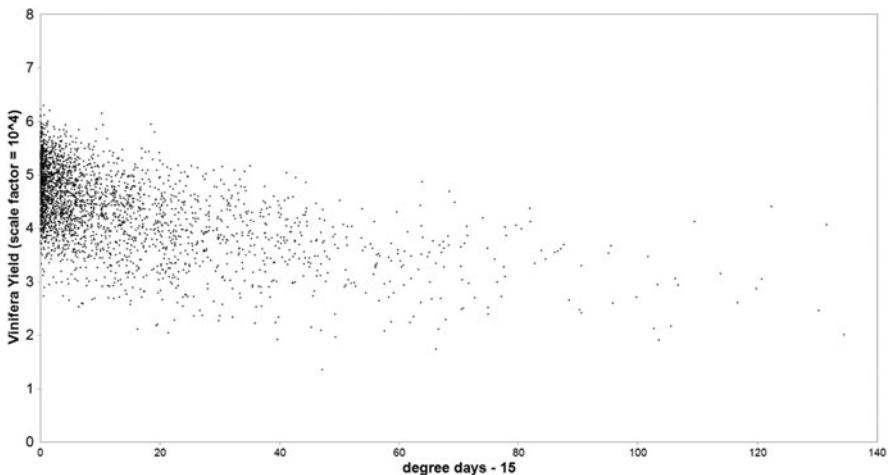


Figure 10. Monte Carlo simulation of aggregate vinifera yield and winter injury degree days -15°C .

Table 3. Detrended yield of vinifera variety, total value (at average price of \$1,345/tonne) and degree days below -15°C from 2003 to 2018

Year	Vinifera detrended yield (tonnes)	Value (\$1345/tonne)	Degree days -15°C
2003	38,021	\$51,138,542	23.5
2004	50,176	\$67,486,459	19.1
2005	32,312	\$43,460,166	24.1
2006	55,557	\$74,724,133	0.0
2007	55,501	\$74,648,256	17.3
2008	58,331	\$78,455,393	3.7
2009	44,426	\$59,752,610	12.6
2010	47,262	\$63,567,817	1.5
2011	53,085	\$71,399,194	13.4
2012	55,447	\$74,576,872	0.0
2013	60,477	\$81,341,664	0.6
2014	38,338	\$51,564,151	48.7
2015	34,306	\$46,141,898	67.8
2016	49,331	\$66,349,966	9.1
2017	56,600	\$76,127,558	4.9
2018	37,425	\$50,336,625	16.5

with other aspects of the contract such as the tic value (payout per degree day or fraction of above strike value) and ultimately a reasonable estimate of the contract price/premium.

Choices with respect to the contract specifications depend largely upon levels of risk aversion and sensitivity to decreases in crop yield/value. Although more sophisticated analyses may result in a more refined conclusion, we note from [Figure 10](#), the scatter diagram of the Monte Carlo simulation, that a lower correlation appears to occur at degree day values below 20. Above a value of 20 degree days, we note a more defined negative linear trend and dependency of yield on degree days. Hence, a call option strike price of 20 degree days is considered.

Employing the 5,000 observations from the Monte Carlo simulation, a linear analysis was performed of the simulated yields associated with -15°C degree days of 20 and above. In total, there were 601 simulated -15°C degree day observations of 20 and above. A regression of the associated simulated yields on degree days greater than 20 garnered a regression coefficient of -116 tonnes per degree day. Assuming again the value of \$1,345 per tonne of grapes, a reasonable tic size specified for the call option would be \$156,020/degree day, or fraction thereof, of 20 and above -15°C degree days.

In summary, the impact on harvest revenues could be examined based on the assumption that the GGO purchased a call option each year on -15°C degree days with a strike price of 20 degree days and a tic size of \$156,020 per degree day.

E. Call option premium (price)

Given that degree days are not a traded asset, risk-free arbitrage option pricing models such as Black Scholes cannot be reasonably applied. The assumptions behind the Black-Scholes option pricing model include complete markets and continuously traded assets. In a complete market, all risks can be traded and priced through a combination of existing financial assets. For example, in a complete market, it is possible to replicate any payoff using a combination of stocks, bonds, and other financial instruments. An incomplete market is a financial market where not all possible risks can be hedged or traded. In other words, an incomplete market is one in which some financial assets or securities are not available for trading or are not priced efficiently, as in the potential application considered here. Hence, some risks cannot be fully hedged or priced because of the lack of available financial instruments that can replicate their payoff, negating the use of Black-Scholes-based pricing models.

In many such cases, the standard is to employ “burn rate” analysis based on Monte Carlo simulation. Pricing is then the expected value of the payoff associated with the option, given the simulation of 5,000 iterations. With the simulation of 5,000 iterations and the assumed contract specifications from earlier, the option payoff for each iteration can be calculated. The average payoff is then assumed to be the option premium. In this case, the average payout, given the contract specifications (strike = 20 degree days, tic = \$156,020/degree day) based on the 5,000 iterations, was \$401,718. Although this value

Table 4. Detrended vinifera yield value hedged and unhedged (2003–2018)

Year	Unhedged value	Call option price	Payout (degree days >20)	Hedged value
2003	\$51,138,542	-\$401,718	\$441,071	\$51,177,895
2004	\$67,486,459	-\$401,718	0	\$67,084,741
2005	\$43,460,166	-\$401,718	\$639,682	\$43,698,130
2006	\$74,724,133	-\$401,718	0	\$74,322,415
2007	\$74,648,256	-\$401,718	0	\$74,246,538
2008	\$78,455,393	-\$401,718	0	\$78,053,675
2009	\$59,752,610	-\$401,718	0	\$59,350,892
2010	\$63,567,817	-\$401,718	0	\$63,166,099
2011	\$71,399,194	-\$401,718	0	\$70,997,476
2012	\$74,576,872	-\$401,718	0	\$74,175,154
2013	\$81,341,664	-\$401,718	0	\$80,939,946
2014	\$51,564,151	-\$401,718	\$4,477,774	\$55,640,207
2015	\$46,141,898	-\$401,718	\$7,457,756	\$53,197,936
2016	\$66,349,966	-\$401,718	0	\$65,948,248
2017	\$76,127,558	-\$401,718	0	\$75,725,840
2018	\$50,336,625	-\$401,718	0	\$49,934,907

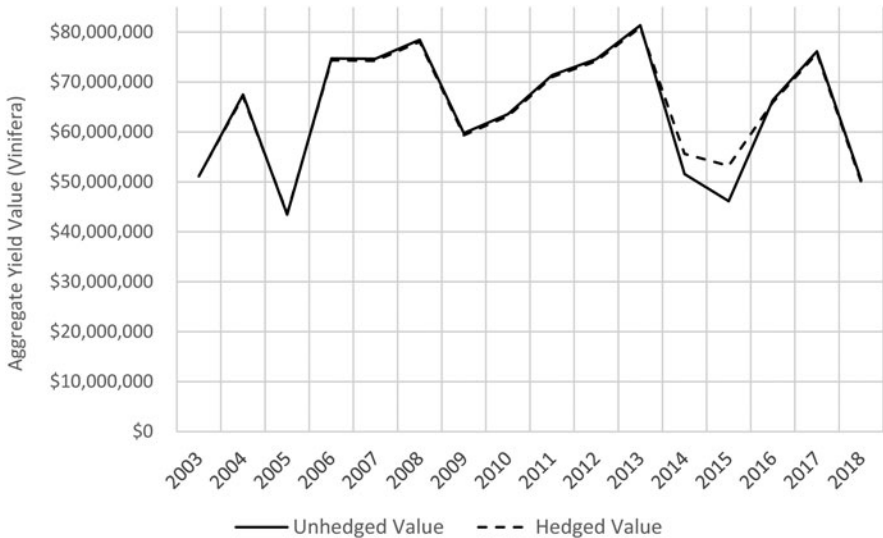


Figure 11. Graph of simulation of unhedged vs. hedged GGO vinifera yield value: 2003–2018.

should be discounted for one year at a risk-adjusted rate of interest, we will assume that any contract supplier commissions would equal or exceed this discount.

Although a Monte Carlo simulation approach and burn rate analysis based on copula function modeling do not result in a solution to the problem of identifying the market price of risk, they do provide some indication of a measure of potential loss due to weather risk and a magnitude of value with respect to the weather derivative considered.

F. Simulated impact of a hedging program

The 2003–2018 schedule of detrended vinifera yield was then employed to simulate the impact of hedging annually with a call option on degree days with a strike price of 20 degree days, tic size of \$156,020/degree day, and a call option price of \$401,718 incurred by the GGO. The results in terms of unhedged versus hedged vinifera yield value are indicated in [Table 4](#). The annual cost of the call option each year and any offset by the option expiring in-the-money (degree days $-15^{\circ}\text{C} > 20$) and hence having a positive payoff are also indicated.

As indicated in [Table 4](#), the option hedge would have had a significant impact in terms of mitigating the cost of winter injury in the years 2003, 2005, and especially in the years 2014 and 2015, when the winter season was particularly severe. Finally, [Figure 11](#) provides a diagram of the vinifera harvest yield value, unhedged and hedged, for the 16 years.

V. Conclusion

Applications of weather derivatives have long been known to suffer from the issue of spatial or geographical basis risk. The distance of a specific producer from a weather

measuring station can have a significant impact on the hedging effectiveness of weather derivatives, as the greater the distance, the less likely the weather conditions will be the same, reducing their effectiveness. Consequently, potential suppliers of weather derivatives to regions and industries such as grape production face additional administrative costs in terms of the need for differing contracts resulting from the idiosyncratic risks of each producer. Along with additional considerations on both the contract buyer and supplier side, this has appeared to inhibit the availability and growth of the use of weather derivatives. In this paper, we consider the possibility of a weather derivatives contract based on the value of aggregate yields for an industry association, the Grape Growers of Ontario, Canada, which represents many individual producers. The possibility of finding the provider of a weather contract based on the aggregate yields of several producers is much greater due to the contract size and minimized contract specifications. Consequently, we explore the sensitivity of aggregate yields to various bioclimatic indices using copula function analysis to determine the most reasonable weather index to base a contract upon. Having identified the best-fitting copula function relating aggregate yields to a measure of winter severity, along with appropriately fitted marginal distributions, we then employ Monte Carlo simulation and burn rate analysis to determine a weather derivative contract price based on reasonable contract specifications. We then simulate the effectiveness of such a contract in hedging aggregate vinifera yields.

Although the approach of aggregation of regional production has the potential to resolve several issues that limit the supply of weather derivatives, an issue that remains is how an association of producers can structure equitable costs and payouts of the weather derivative hedging program for individual member producers, given they face idiosyncratic basis risk. Although weather conditions are often not dissimilar between the three major regions comprising the members of the Grape Growers Association of Ontario, a simple approach may be to structure such payouts based upon a factor of distance from the weather station employed for measurement. Other more sophisticated approaches could take into account a number of geographical measures such as altitude, latitude, and longitude, or even the use of a weather index based upon a “portfolio” of weather measuring stations (Norton, Turvey, and Osgood, 2013). There is no doubt that individual producer basis risk may remain a challenge for an industry association looking for approval to undertake such a hedging program on behalf of its members. Clement et al. (2018) provide a recent review of the literature on the issue of basis risk.

When designing the potential hedging program, we examined several bioclimatic indices in order to determine which were most significantly correlated with aggregate yields to base a weather contract upon. Future research could involve the use of multivariate copula function modeling to design an aggregate bioclimatic index constructed from individual indices that would capture the impact of several weather-related risk factors. Santos et al. (2020), for example, employ principal component analysis in deriving a combined dryness and Huglin bioclimatic index to examine the impact of climate change on viticulture in Portugal, whereas Kavianpour, Seyedabadi, and Moazami (2018) employ a similarly combined bioclimatic index to measure drought in Iran based on copula modeling. Finally, willingness-to-pay for weather derivatives on the part of grape growers is an area

that requires future research. The level of risk aversion (perhaps captured by the size of the industry participant) is one factor that has been shown to be important in the willingness-to-pay for weather derivatives. Larger producers may be more able to “self-assure” smooth revenues over time and hence place less value on a weather derivative application. As noted in Section I, there is extensive research on willingness-to-pay for weather derivatives, but the studies are largely focused on agriculture in developing countries.

Looking at the potential future of weather derivatives, innovations in the use of blockchain cryptography have the potential to contribute significantly to their supply and ease of use (Kshetri, 2021; Aleksieva, Valchanov, and Huliyan, 2020). Indeed, it has been estimated that blockchain and smart contract technology could reduce administrative costs by as much as 30% on the part of insurers (De, 2018). AccuWeather, a U.S. media company that provides commercial weather forecasting services worldwide, has recently established a node on the Chainlink blockchain in order to provide weather information that is cryptographically signed when uploaded to the blockchain for use in smart contracts (PYMNTS, 2021). Arbol is a recently established firm that is the provider of marketplace technology supporting parametric risk transfer and weather insurance, utilizing smart contracts (Evans, 2021). Developments also include the increasing use of satellite data for weather and climate measurements (Black et al., 2016).

Acknowledgments. The authors wish to thank an anonymous reviewer for their insightful and helpful comments in improving the paper. The authors declare no competing interests.

References

- Abebe, T. H., and Bogale, A. (2014). Willingness to pay for rainfall based insurance by smallholder farmers in Central Rift Valley of Ethiopia: The case of Dugda and Mieso Woredas. *Asia Pacific Journal of Energy and Environment*, 1(2), 121–155.
- Adelsheim, D., Busch, C., Catena, L., Champy, B., Coetzee, J., Coia, L., and Torres, M. (2016). Climate change: Field reports from leading winemakers. *Journal of Wine Economics*, 11(1), 5–47.
- AGRICORP (2022). Production insurance: Grape and grapevines. Available at <https://www.agricorp.com/en-ca/Programs/ProductionInsurance/Grapes/Pages/Overview.aspx>.
- Ahmed, A., Alkahtani, M., El-Tamimi, A. M., Kaid, H., and Abidi, M. H. (2021). Developing a model for safety risk assessment under uncertainty for the manufacturing industry: A case study of pole factory hazards in Riyadh, Saudi Arabia. *Mathematical Problems in Engineering*, 2021, 1–13.
- Akter, S., Krupnik, T. J., Rossi, F., and Khanam, F. (2016). The influence of gender and product design on farmers’ preferences for weather-indexed crop insurance. *Global Environmental Change*, 38, 217–229.
- Aleksieva, V., Valchanov, H., and Huliyan, A. (2020). Smart contracts based on private and public blockchains for the purpose of insurance services. Paper presented at the 2020 International Conference Automatics and Informatics (ICAI), Varna, Bulgaria, October 1–3. Available at <https://ieeexplore.ieee.org/document/9311371>.
- Alexandridis, A., and Zapranis, A. (2013). *Weather Derivatives: Modeling and Pricing Weather-Related Risk*. New York: Springer.
- Ali, A. (2013). Farmers’ willingness to pay for index based crop insurance in Pakistan: A case study on food and cash crops of rain-fed areas. *Agricultural Economics Research Review*, 26(2), 241–248.
- Ashenfelter, O., and Storchmann, K. (2016). Climate change and wine: A review of the economic implications. *Journal of Wine Economics*, 11(1), 105–138.
- Black, E., Greatrex, H., Young, M., and Maidment, R. (2016). Incorporating satellite data into weather index insurance. *Bulletin of the American Meteorological Society*, 97(10), ES203–ES206.

- Bokusheva, R. (2011). Measuring dependence in joint distributions of yield and weather variables. *Agricultural Finance Review*, 71(1), 120–141.
- Bokusheva, R. (2018). Using copulas for rating weather index insurance contracts. *Journal of Applied Statistics*, 45(13), 2328–2356.
- Bramble, L., Cullen, C., Kushner, J., and Pickering, G. (2007). The development and economic impact of the wine industry in Ontario, Canada. In G. Campbell and N. Guibert (eds.), *Wine, Society, and Globalization*, 63–86. New York: Palgrave Macmillan.
- Budhathoki, N. K., Lassa, J. A., Pun, S., and Zander, K. K. (2019). Farmers' interest and willingness-to-pay for index-based crop insurance in the lowlands of Nepal. *Land Use Policy*, 85, 1–10.
- Carter, M., De Janvry, A., Sadoulet, E., and Sarris, A. (2014). Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling. FERDI, Development Policies Working Paper No. 111, September. Unpublished manuscript. Available at <https://ferdi.fr/dl/df-klB5hYBaUiR2Vysm2cH5DfCP/ferdi-p111-index-based-weather-insurance-for-developing-countries-a-review.pdf>.
- Clement, K. Y., Botzen, W. W., Brouwer, R., and Aerts, J. C. (2018). A global review of the impact of basis risk on the functioning of and demand for index insurance. *International Journal of Disaster Risk Reduction*, 28, 845–853.
- Cortina, E., and Sánchez, I. (2013). Hedging late frost risk in viticulture with exotic options. *Agricultural Finance Review*, 73(1), 136–160.
- Cyr, D., and Kushner, J. (2022). Microclimate tipping points in bioclimatic indices in the Niagara region of Canada. Brock University, Canada. Unpublished manuscript.
- Cyr, D., and Kusy, M. (2007). Canadian ice wine production: A case for the use of weather derivatives. *Journal of Wine Economics*, 2(2), 145–167.
- Cyr, D., Kusy, M., and Shaw, A. B. (2008). The potential use of weather derivatives in the viticulture industry. *Economia e diritto agroalimentare*, 13(3), 67–81.
- Cyr, D., Kusy, M., and Shaw, A. (2010). Climate change and the potential use of weather derivatives to hedge vineyard harvest rainfall risk in the Niagara region. *Journal of Wine Research: Climate Change and the Wine Industry*, 21(2–3), 207–227.
- Cyr, D., Kwong, L., and Sun, L. (2017). An examination of tail dependence in Bordeaux futures prices and Parker ratings. *Journal of Wine Economics*, 12(3), 252–266.
- Cyr, D., Kwong, L., and Sun, L. (2019). Who will replace Parker? A copula function analysis of Bordeaux en primeur wine raters. *Journal of Wine Economics*, 14(2), 133–144.
- De, N. (2018). Fitch ratings: Blockchain is a potential game-changer' for insurers. *CoinDesk*, April 25. Available at <https://www.coindesk.com/markets/2018/04/26/fitch-ratings-blockchain-is-a-potential-game-changer-for-insurers/>.
- Demberger, A. (2017). Risk rises in wine country as weather becomes increasingly volatile. *Risk & Insurance*, November. Available at <https://riskandinsurance.com/risk-rises-wine-country/>.
- Edwards, M. J., and Simmons, P. (2004). Preliminary results for the measurement of willingness to pay for climate derivatives. Presented at the 48th Annual Conference of the Australian Agricultural and Resource Economics Society, Melbourne, Australia, February 11–13. Available at https://www.researchgate.net/publication/261671816_Preliminary_results_for_the_measurement_of_willingness_to_pay_for_climate_derivatives.
- Evans, S. (2021) Arbol's *Captive+Parametric* to help corporations manage climate risk. *Artemis.bm*, August 12. Available at <https://www.artemis.bm/news/arboll-captive-parametric-corporations-manage-climate-risk/>.
- Fahad, S., and Jing, W. (2018). Evaluation of Pakistani farmers' willingness to pay for crop insurance using contingent valuation method: The case of Khyber Pakhtunkhwa province. *Land Use Policy*, 72, 570–577.
- Fonta, W. M., Sanfo, S., Kedir, A. M., and Thiam, D. R. (2018). Estimating farmers' willingness to pay for weather index-based crop insurance uptake in West Africa: Insight from a pilot initiative in Southwestern Burkina Faso. *Agricultural and Food Economics*, 6(1), 1–20.
- Goodwin, B. K., and Hungerford, A. (2015). Copula-based models of systemic risk in U.S. agriculture: Implications for crop insurance and reinsurance contracts. *American Journal of Agricultural Economics*, 97(3), 879–896.
- Grape Growers of Ontario (2019). 71st Annual Report, Year ending January 31, 2019. *Grape Growers of Ontario*. Available at <https://grapegrowersofontario.com/media/idrjozq2/71st-annual-report-final-2019.pdf>.

- Habibi, H., and Habibi, R. (2016). Applications of simulation-based methods in finance: The use of model-risk software. *Journal of Advanced Studies in Finance*, 7(1), 82–89.
- Hasebe, T. (2013). Copula-based maximum-likelihood estimation of sample-selection models. *The Stata Journal*, 13(3), 547–573.
- Huglin, M. P. (1978). Nouveau mode d'évaluation des possibilités héliothermiques d'un milieu viticole. *Comptes Rendus de l'Académie d'Agriculture de France*, 64, 1117–1126.
- Johnson, L. (2021). Paying ex gratia: Parametric insurance after calculative devices fail. *Geoforum*, 125, 120–131.
- Jones, G. V., Edwards, E. J., Bonada, M., Sadras, V. O., Krstic, M. P., and Herderich, M. J. (2022). Climate change and its consequences for viticulture. In A. G. Reynolds (ed.), *Managing Wine Quality*, 727–778. Sawston, UK: Woodhead Publishing.
- Kavianpour, M., Seyedabadi, M., and Moazami, S. (2018). Spatial and temporal analysis of drought based on a combined index using copula. *Environmental Earth Sciences*, 77(22), 1–12.
- Kong, R., Turvey, C. G., He, G., Ma, J., and Meagher, P. (2011). Factors influencing Shaanxi and Gansu farmers' willingness to purchase weather insurance. *China Agricultural Economic Review*, 3(4), 423–440.
- Kshetri, N. (2021). Blockchain-based smart contracts to provide crop insurance for smallholder farmers in developing countries. *IT Professional*, 23(6), 58–61.
- Lin, J., Boyd, M., Pai, J., Porth, L., Zhang, Q., and Wang, K. (2015). Factors affecting farmers' willingness to purchase weather index insurance in the Hainan Province of China. *Agricultural Finance Review*, 75(1), 103–113.
- Lin, X., and Kwon, W. J. (2020). Application of parametric insurance in principle-compliant and innovative ways. *Risk Management and Insurance Review*, 23(2), 121–150.
- Liu, X., Tang, Y., Ge, J., and Miranda, M. J. (2019). Does experience with natural disasters affect willingness-to-pay for weather index insurance? Evidence from China. *International Journal of Disaster Risk Reduction*, 33, 33–43.
- Lourme, A., and Maurer, F. (2017). Testing the Gaussian and Student's t copulas in a risk management framework. *Economic Modelling*, 67, 203–214.
- McCarthy, N. (2003). Demand for rainfall-index based insurance: A case study from Morocco. International Food Policy Research Institute, EPTD Discussion Paper No. 106, July. Download from https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwi5yPGO4dKAAxVGk4kEHfZsDUUQFnoECA8QAQ&url=https%3A%2F%2Fpageconsearch.umn.edu%2Frecord%2F16084%2Ffiles%2Fep030106.pdf&usq=AOvVaw3_t_4m__R0ktrbxtqR_MV5&opi=89978449.
- McPhee, J. E., Maynard, J. R., Aird, P. L., Pedersen, H. H., and Tullberg, J. N. (2016). Economic modelling of controlled traffic for vegetable production. *Australian Farm Business Management Journal*, 13, 1–17.
- Mercer, C. (2018). Extreme weather becoming the new normal – study. *Decanter*, April 19. Available at <https://www.decanter.com/wine-news/climate-change-in-vineyards-extreme-weather-becoming-new-normal-388721/>.
- Norton, M. T., Turvey, C., and Osgood, D. (2013). Quantifying spatial basis risk for weather index insurance. *The Journal of Risk Finance*, 14(1), 20–34.
- Odening, M., and Shen, Z. (2014). Challenges of insuring weather risk in agriculture. *Agricultural Finance Review*, 74(2), 188–199.
- Pasaribu, K. N., Lambert, L. H., Lambert, D. M., English, B. C., Clark, C. D., Hellwinckel, C., Boyer, C. N., and Aaron Smith, S. (2021). Profitability of irrigating for corn, cotton, and soybeans under projected drought scenarios in the Southeastern United States. *Irrigation Science*, 39, 315–328.
- Pickering, K., Pickering, G. J., Inglis, D., Shaw, T., and Plummer, R. (2012). Innovation and adaptation in the Ontario grape and wine industry: An integrated, transdisciplinary response to climate change. Brock University Working Paper No. ESRC-2012-002. Available at <https://dr.library.brocku.ca/bitstream/handle/10464/4149/Working%20paper%20-%20ESRC-2012-002.pdf?sequence=1>.
- PYMNTS (2021). Smart contracts get weather-savvy with AccuWeather on the blockchain. *PYMNTS*, December 15. Available at <https://www.pymnts.com/blockchain/2021/smart-contracts-get-weather-savvy-with-accuweather-on-blockchain/>.
- Roussis, D., Parara, I., Gournari, P., Moustakis, Y., Dimitriadis, P., Iliopoulou, T., and Karakatsanis, G. (2017). Energy, variability and weather finance engineering. Presented in the EGU General Assembly Conference Abstracts (p. 16919). Conference held April 23–28 in Vienna, Austria.

- Ryberg, M. W., Hauschild, M. Z., Wang, F., Averous-Monnelly, S., and Laurent, A. (2019). Global environmental losses of plastics across their value chains. *Resources, Conservation and Recycling*, 151, 104459.
- Salgueiro, A. M. (2019). Weather index-based insurance as a meteorological risk management alternative in viticulture. *Wine Economics and Policy*, 8(2), 114–126.
- Salgueiro, A. M., and Tarrazon-Rodon, M. A. (2021). Is diversification effective in reducing the systemic risk implied by a market for weather index-based insurance in Spain? *International Journal of Disaster Risk Reduction*, 62, 102345.
- Santos, M., Fonseca, A., Fraga, H., Jones, G. V., and Santos, J. A. (2020). Bioclimatic conditions of the Portuguese wine denominations of origin under changing climates. *International Journal of Climatology*, 40(2), 927–941.
- Seccia, A., Santeramo, F. G., and Nardone, G. (2016). Risk management in wine industry: A review of the literature. *BIO Web of Conferences*, 7, 03014. Available at https://www.bio-conferences.org/articles/bioconf/pdf/2016/02/bioconf-oiv2016_03014.pdf.
- Senapati, A. K. (2020). Insuring against climatic shocks: Evidence on farm households' willingness to pay for rainfall insurance product in rural India. *International Journal of Disaster Risk Reduction*, 42, 101351.
- Shaw, T. (2017). Climate change and the evolution of the Ontario cool climate wine regions in Canada. *Journal of Wine Research*, 28(1), 13–45.
- Simmons, P., Edwards, M., and Byrnes, J. (2007). Willingness to pay for weather derivatives by Australian wheat farmers (No. 686-2016-47127). Presented at the 101st EAAE Seminar Management of Climate Risks in Agriculture, Berlin, Germany, July 5–6, doi: [10.22004/ag.econ.9262](https://doi.org/10.22004/ag.econ.9262).
- Sklar, A. (1973). Random variables, joint distribution functions, and copulas. *Kybernetika*, 9(6), 449–460.
- Trivedi, P. K., and Zimmer, D. M. (2005). Copula modeling: An introduction for practitioners. *Foundations and Trends in Econometrics*, 1(1), 1–111.
- Turvey, C. G., and Kong, R. (2010). Weather risk and the viability of weather insurance in China's Gansu, Shaanxi, and Henan provinces. *China Agricultural Economic Review*, 2(1), 5–24.
- Turvey, C., Weersink, A., and Celia Chiang, S. (2006). Pricing weather insurance with a random strike price: The Ontario Icewine Harvest. *American Journal of Agricultural Economics*, 88(3), 696–709.
- Van Leeuwen, C., and Darriet, P. (2016). The impact of climate change on viticulture and wine quality. *Journal of Wine Economics*, 11(1), 150–167.
- VQA (2019). Ontario Wine Appellation Authority, Ontario Appellations, <https://vqaontario.ca/ontario-appellations/>.
- Wairimu, E., Obare, G., and Odendo, M. (2016). Factors affecting weather index-based crop insurance in Laikipia County, Kenya. *Journal of Agricultural Extension and Rural Development*, 8(7), 111–121.
- Winkler, A. J. (1962). *General Viticulture*. Berkeley, CA: University of California Press.
- Woodard, J. D., and Garcia, P. (2008). Weather derivatives, spatial aggregation, and systemic risk: Implications for reinsurance hedging. *Journal of Agricultural and Resource Economics*, 33(1), 34–51.
- Yandell, A. W. (2012). The potential application of weather derivatives to hedge harvest value risk in the Champagne region of France. Claremont McKenna College, CMC Senior Theses. Available at https://scholarship.claremont.edu/cgi/viewcontent.cgi?article=1365&context=cmc_theses.
- Zara, C. (2010). Weather derivatives in the wine industry. *International Journal of Wine Business Research*, 23(3), 222–237.