THREE TOPICS IN WEATHER INDEX INSURANCE

A Thesis

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Master of Science

by

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ABSTRACT

This paper presents three papers on the topic of weather index insurance, the practice of mitigating risk according to objective measurements of weather conditions. The topic has a simple premise, but the implementation is anything but. The weather/crop yield relationship, and therefore risk, is not a straightforward function, and weather observations seldom align themselves for easy analysis. Being a relatively new technology, there are of course problems with implementation and rich opportunities for research and analysis.

The first topic is to present the internet site that enabled access to the weather data. It is groundbreaking and among the first of its kind. The second topic regards plant disease risks when faced with risks in combination, specifically regards to heat and drought risk occurring simultaneously, and the last topic is an algorithmic approach to the problem of geographical basis risk.

BIOGRAPHICAL SKETCH

Michael Norton was born on September 16, 1978 in Austin, Texas to James F. and Lynne L. Norton. He has an older brother, James, and a younger sister, Lesley.

Early life involved much moving and resettlement, living with his family in Texas, California, and Delaware before settling in Langhorne, PA in 1987, from whence he graduated from Neshaminy High School in 1995.

After a postgraduate year at The Peddie School in Hightstown, NJ, Michael matriculated into Carnegie Mellon University in Pittsburgh, PA. Majoring in Information and Decision Systems, Michael graduated from CMU in December of 2000.

Michael worked for a year at a subsidiary of Siemens in Malvern, PA, and afterwards joined the Peace Corps. As a Peace Corps Volunteer in Malawi, Michael taught math, history, and life skills at a secondary school for over two years. Upon completion of service, Michael worked at the Population Studies Center of the University of Pennsylvania on a social research project based in Malawi.

Michael began his studies at Cornell University in the fall of 2006.

To my parents

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First thanks goes to my advisory committee, Professors Calum Turvey and Vicki Bogan, for their help and guidance in the conception of this paper.

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LIST OF ABBREVIATIONS

APHIS – Animal and Plant Health Inspection Service (USDA)

CDD – Cooling Degree Days

GDD – Growing Degree Days

HDD – Heating Degree Days

NOAA – National Oceanic and Atmospheric Administration

OTC – Over the counter

SQL – Structured Query Language

USDA – United States Department of Agriculture

WRMA – Weather Risk Management Association

LIST OF SYMBOLS

Chapter 3:

x - an ordinary input (e.g fertilizer)

$\alpha_i(\ )$ - random coefficients of the production function

ω - a specific weather event

$H(\omega)$ - stochastic household production function

ψ - a weather/currency converter

Chapter 4:

p - the price per bushel of the crop in question

Y – normal yield

Y^* - yield under stress

$f(R,T,t)$: The frequency of a given weather event with respect to rainfall (R), temperature (T), and time (t).

$g(\Theta)$: The probability of infection given favorable weather conditions.

Chapter 5:

P_x – payout at station x

φ - distance between the two stations

α_x - the altitude at each station,

ω_x - the latitude at each station, and

λ_x - the absolute value of the longitude of each station

Chapter 1 - Introduction

This document is the culmination of two years of work on the topic of weather index insurance, the practice of mitigating risk according to objective measurements of weather conditions. The topic has a simple premise, but the implementation is anything but. The weather/crop yield relationship, and therefore risk, is not a straightforward function, and weather observations seldom align themselves for easy analysis. Being a relatively new technology, there are of course problems with implementation and rich opportunities for research and analysis.

Although there is an established market for weather derivatives on the Chicago Mercantile Exchange (CME) for hedging weather-based risk, the products might be considered to be more useful for industries like energy which primarily operate in the cities in which the indexes are collated and have a more definitive relationship to marginal gradations in temperature. It is still not understood how to define what weather conditions create risk for agricultural producers and how precisely to model those risk conditions at diverse locations, problems that will need to be overcome before widespread adoption of weather index insurance can commence. What follows is a series of three papers, prepared or intended for publication, that attempt to ameliorate those problems.

The History of Weather Index Insurance

The energy industry has long been observed to be sensitive to variations in weather conditions. Energy suppliers will prosper in a cold winter through a high volume of energy sold, but is stifled in an abnormally temperate winter. The benchmark is generally considered to be 65° F, a temperature above which people demand electricity to cool buildings and below which demand energy (coal, natural gas, electricity) for heating purposes. These revenue streams are highly variable and highly dependent on the severity of a season. Traditionally, this wasn't a problem because suppliers faced no competition in a market and received government price guarantees. With the advent of deregulated energy markets in the 1990s, energy firms found the need to hedge against weather risk, and thus the weather derivatives market was born. An early pioneer in the weather derivatives market was Enron, through its Enron Online unit.

In its current form, the market at the CME will allow an energy supplier to purchase a non-asset based futures contract pegged to a weather index. For example, an energy supplier may wish to write an option contract that will pay off if a summer is sufficiently hot, reasoning that in such conditions revenues will be healthy enough so that they will happily cover the cost of the option payout. If the summer is cool, the energy company would generate less revenue from the sale of electricity, but will pocket the premium for writing the contract and thus smooth their revenue stream. The CME now includes 645 weather products for 35 cities worldwide, as well as hurricane indices for the East and Gulf Coasts. In addition to the futures and options traded on the CME, third-party vendors also sell customizable over-the-counter contracts for virtually any combination of temperature event imaginable. As of 2005, Turvey reports that 4000 transactions occurred that were worth $8 bn (Lyon 2004).

Organizations like the Weather Risk Management Association (WRMA) now exist which bring together principals from the meteorology, insurance and finance industries to accomplish such goals as establishing standards for credit and expanding the weather market geographically. The concepts developed for the energy industry also apply to other fields, and much of the current research involves applying the successful strategies developed for the energy industry for other weather-sensitive industries.

The successful development of methods for pricing weather index insurance contracts will likely have profound impacts on developing countries, which are highly dependent on agriculture. The sheer number of smallholder farms in these countries precludes the dissemination of traditional adjustment-based insurance policies even though impoverished farmers bear the full brunt of climatic variability. A successful implementation of a weather index insurance program would likely have profound implications for improving the livelihood of farmers in these countries by preventing them from falling into a “poverty trap” when faced with crop losses due to adverse weather conditions. (Skees 2008)

Objectives

The purpose of this research is to refine and develop methods for pricing weather index insurance by taking observations of a stochastic process. The markets described above for the CME and any over-the-counter (OTC) represent the foundations of weather index insurance or any weather derivative product. However, they require strict assumptions. First, risk events are only considered as separate entities, even though stress events often have more profound negative impacts on crops when happening simultaneously. Often, calculating risk on single events is incomplete, especially in regard to plant pathogens like fungi, molds, and insects that require specific meteorological criteria for their presence. Developing a method for pricing insurance for joint probabilities is necessary for the successful wide scale adoption of weather index insurance.

Second, these products price their products at a single location and assume that weather patterns at that fixed location are adequate to describe weather conditions at the site of the insured event. This is not always the case and an understanding of conditions at the insured location is often required. The difference in risk profile between the measured location and the insured location is known as geographic basis risk, and it is a problem which to this date has not been adequately resolved.

Third, the process to model single, joint, or geographic risk profiles is computationally intense and requires the manipulation of large amounts of weather data. The computational intensity is unto itself a problem and the pursuit of an algorithmic, generally applicable, and flexible tool to assist in computation and analyses is unto itself a worthwhile pursuit. Thus, in order to design and price weather insurance for multiple or single events with independent or joint risks, while taking into consideration basis risk, a major contribution of this research is the design and web placement of a computer program which we refer to as Weather Wizard.

This thesis extends the existing literature in three ways: by introducing an interactive web tool for further analysis, by providing a measure of joint weather events in regard to pest risks, and beginning analysis of geographic spread of risk.

Internet Tool

The first contribution of this thesis is the development of an internet tool to facilitate analysis of weather observations. Given the virtually limitless number of possibilities for contract design, a flexible and accessible tool was needed to facilitate understanding of the nuances thereof. Thus, through a grant from the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA), the Weather Wizard website was born.

Weather Wizard contains data from the (NOAA) for over 25,000 stations across the U.S., with observations stretching back more than 100 years in some cases.

It contains information on four different weather indexes – rainfall, high temperatures, low temperatures, and mean temperatures.

The advantage of offering the functions of Weather Wizard in a web format is the absolute transparency it offers. Although not allowed to display individual weather observations, it does allow any argument made in an academic context to be instantly verified by anyone with an internet connection. All of the functionality presented in this thesis has been programmed into Weather Wizard, and it is possible to retrace the exact steps taken in analysis.

Furthermore, Weather Wizard not only allows accessibility but allows the user absolute flexibility to select the parameters for analysis. Too often weather management tools – like the MSI Guaranteed Weather website – only offer observations from the most recent years (starting 1950) and in certain weather stations. Some of the major variations we have seen occurred in periods like the Dust Bowl of the 1930s, and to censor data before a certain date is to remove a major source of information. Likewise, Weather Wizard allows for the selection of any weather station for which the NOAA provides data, no matter how few years of data exist (a decision that will have important implications for the discussion on geographic basis risk.)

Although Weather Wizard has until now been used mainly by researchers in-house at Cornell University, it has the potential to be used by not only researchers at outside institutions but the principals in the contract themselves. Weather Wizard is not intended to be a commercial enterprise, but the concepts used are of undoubted interest to the insurance and financial industries.

Joint Risk

As valuable as a weather index might be, it does not include all of the potentially valuable information that we may have about growing conditions at a specific station. Any attempt to mitigate local basis risk by examining the weather/crop yield relationship is necessarily incomplete without considering the interaction between heat and precipitation stress events, as the presence of one often compounds the negative effects to crop yields. Indeed, Mittler (2006) states that plants subject to a combination of weather risks will have a “molecular and metabolic response … [that] is unique and cannot be extrapolated from the response of plants to each of these different stresses applied individually.”

In addition, risk criteria for weather index insurance are often ill-defined and therefore subject to imperfect hedge ratios. By taking our risk parameters directly from the scientific literature and basing our yield loss estimates on crop damage rather than a production function we may avoid some of the more serious problems with weather index insurance.

Geographic Basis Risk

Berg and Schmitz (2008) state that “geographical basis risk could probably be reduced substantially by utilizing the information of several surrounding weather stations instead of only the nearest one.” With the wealth of data available via Weather Wizard, it is possible to begin analysis of geographic basis risk.

Currently, farmers in rural locations would be expected to purchase weather index insurance indexed to a certain weather station in close proximity to their farm. This station would need to have similar weather patterns and be well-established with many years of data to accurately price historical frequencies. Unfortunately, the choice is not always clear as to which station would properly mimic the risk conditions present at the farm, or if a distant location will even be able to properly mimic risk at the farm site in question.

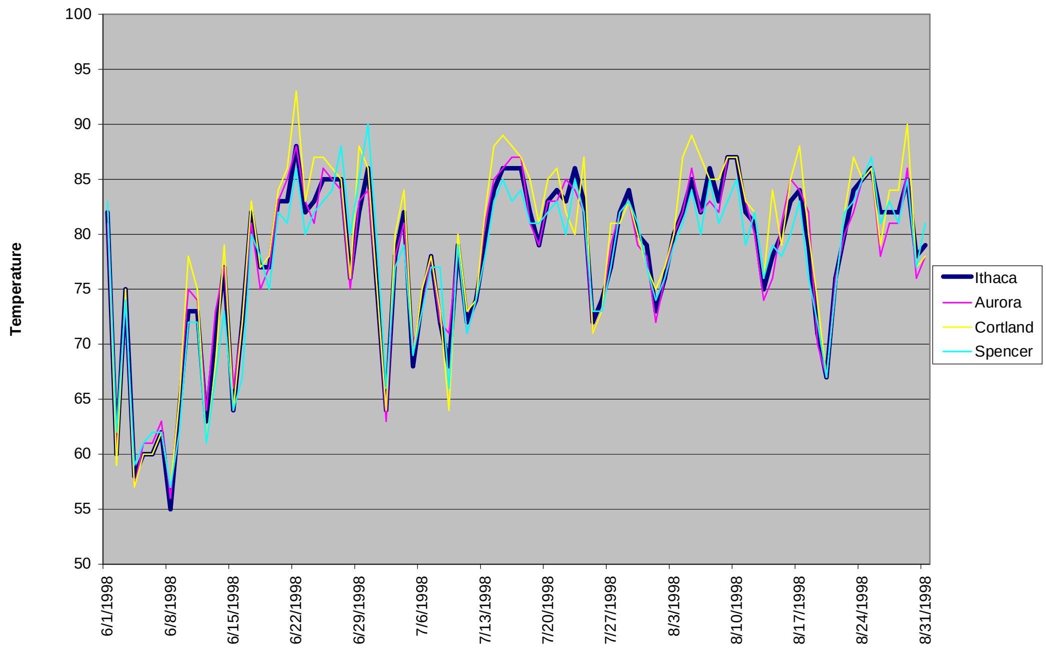

Figure 1: Daily maximum temperature observations for Ithaca, NY and three closest weather stations for June-August, 1998.

For illustration, Figure 1and Figure 2 use the exact same data on different scales. Figure 1 shows daily temperatures moving in virtual lockstep for Ithaca, NY and the three closest stations from the period June 1st – August 31st. However, when we censor that data to consider a risk event (temperatures in excess of 85° F), the distribution becomes very different, and the differential in risk events become more apparent. A farmer in close proximity to the Cortland weather station received far more exposure to high temperatures than a farmer in Ithaca, revealing an ambiguity for any farmers located in between the two stations (which are 20 miles apart.) But this example is just in a small geographic area for a single growing season, and an effort needs to be made to look at the problem of geographic basis risk in a more systematic fashion.

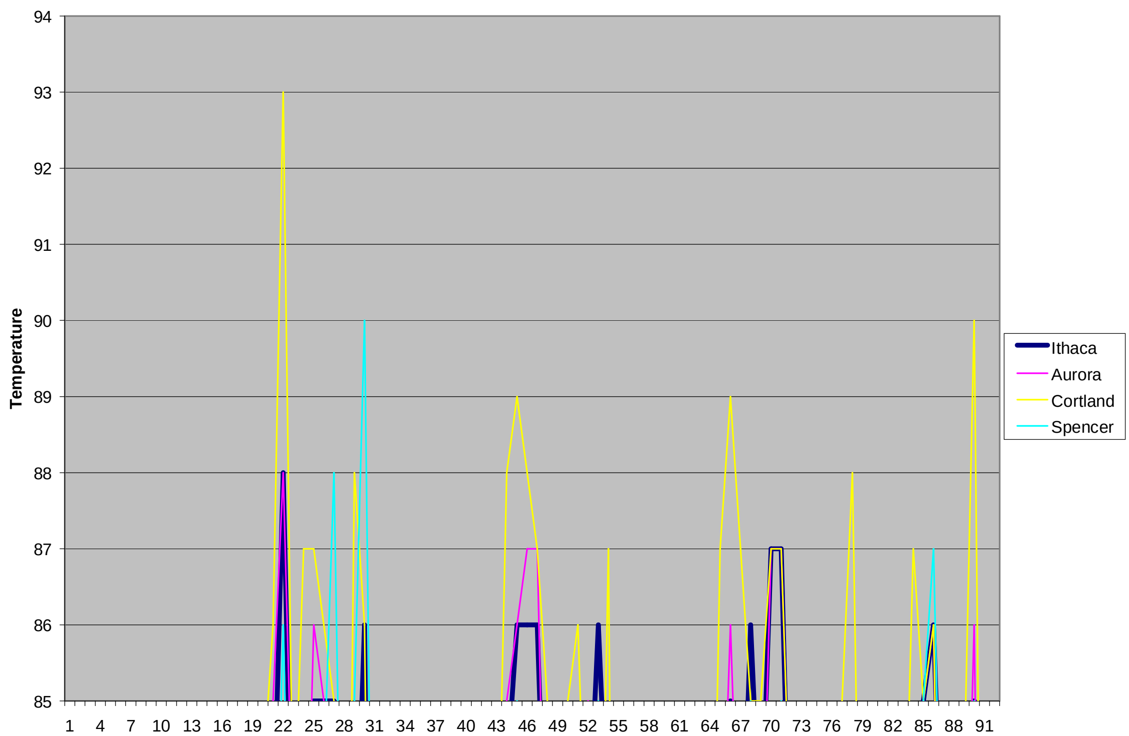

Figure 2: Daily temperature observations censored to display potential risk events.

Organization

Chapter 2 provides a background of conceptual issues in weather index insurance, provides a technical definition for weather index insurance contracts, and outlines the current state of research.

A full treatment of the Weather Wizard website is presented in Chapter 3, which was published in the April 2008 issue of the *Agricultural and Resource Economics Review.*

Chapter 4 considers the simultaneous occurrence of risk events with regard to specific plant disease risks: Karnal bunt of wheat, Stewart's disease and silk cut in corn. In each case, risk parameters are derived from the plant disease literature and adapted to price insurance premiums based on the historical incidence of weather patterns and disease infection rates.

Our task in Chapter 5 was to uncover a systematic relationship in the spatial relationships between stations and begin to price contracts for locations where no weather station exists, and whether or not risk premiums can be correlated to simple geographic variables.

Finally, a summary of major points and concepts is presented with conclusions in Chapter 6.

For reference, two appendixes are included after Chapter 7, one with code samples of Weather Wizard, and one with technical specifications used in the creation of the website.

Chapter 2 – Conceptual Issues In Weather Index Insurance

Although we refer to weather index insurance as a single concept, to do so glosses over the complexity therein. There are a great many options for writing contracts based on a few simple weather indexes, and that is in part because of the vastly different natures of the indexes. The raw data for temperatures and precipitation is distributed in very different fashions and any contract written must do so within the parameters of the variability of the index while also keeping in mind the specific risk requirements of the insuree.

For illustration, the following two figures – Figure 3 and Figure 4 – illustrate temperature and rainfall, respectively.

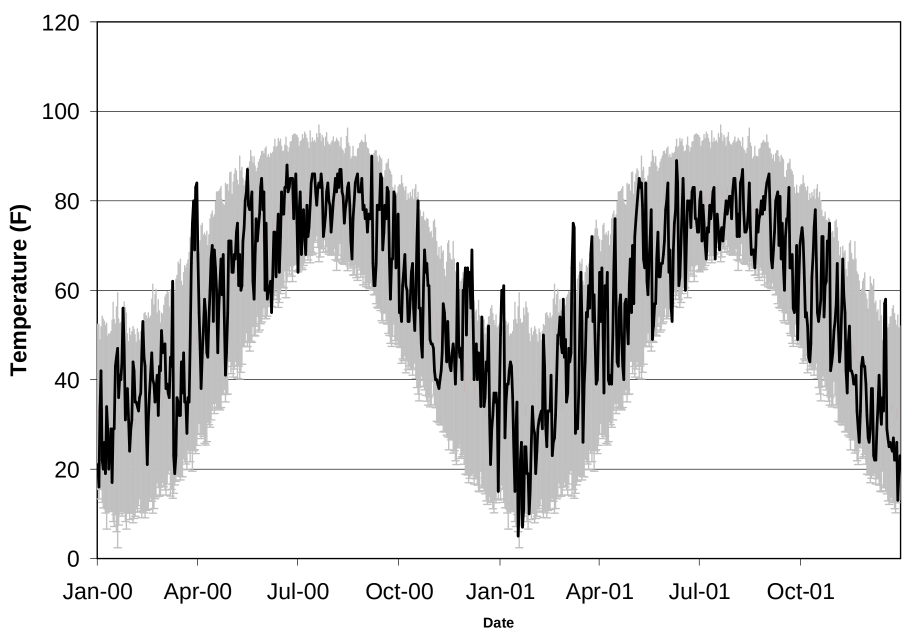

Figure 3: Daily maximum temperature observations for two year period (Jan 1st 2000 – Dec 31st 2001) at Ithaca, NY station (with confidence intervals.)

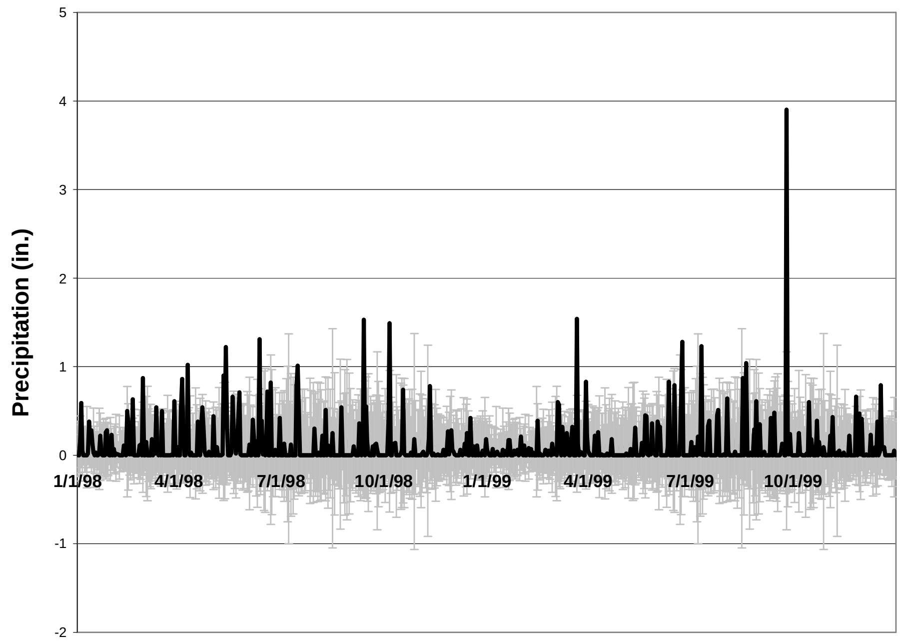

Figure 4: Daily precipitation observations for two year period (Jan 1st 2000 – Dec 31st 2001) at Ithaca, NY (with confidence intervals.)

Daily maximum temperature observations are cyclical throughout the year, peaking in July and reaching a nadir in January and February. The gray confidence intervals do not reflect a constant variance as the variance in summer temperatures is much less than winter, but is somewhat contiguous. It may differ from season to season but does not contain any obvious spikes during which individual days are considerably more variable than others.

Rainfall measurements, by contrast, reveal a fairly constant mean throughout the year. The variability decreases in the winter months, which is probably due to the fact that precipitation in Ithaca will often instead be counted in the snowfall data for those months. Certainly we can say that the variability is not as contiguous as individual days will often have abnormal levels of variance, probably due to the effects of a few large observations. (We can see one here in the second year of study – Ithaca recorded 3.9” of precipitation on September 25th, 2001) The presence of rain is episodic and unpredictably random in its invocation, and the variability includes the zero value in all instances because of the large number of observations in which there was no daily rainfall.

We want to properly design insurance products to cover a rare event. The rarity itself is variable, whether it be a 1 in 10 year event or a 1 in 20 year event, all monies paid out by the policy must also be paid in. A properly designed insurance product will not only provide an accurate measure of risk but also consider the requirements of the policy holder. This becomes difficult when we consider all of the potential parameters in a weather contract, frequency, intensity, location, and duration.

It is the variable distribution of these risk events that we want to insure against, and they may be designed in several ways. One example comes from the World Bank project underway in Malawi, which offers drought insurance to subsistence farmers. For rainfall amounts under a certain threshold (120 mm), the policy pays a variable amount until a lower threshold (50 mm) of rainfall is reached, at which point it is considered that the crop was a total loss and further compensation in unnecessary.

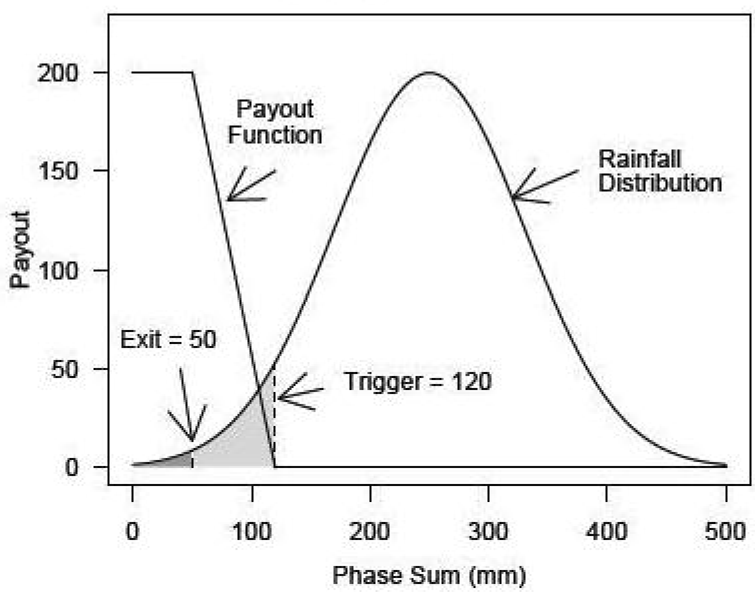

Figure 5: Payoff schedule for precipitation risk event (from Shirley 2008)

Contract Design – Temperature Contracts

We design contracts to insure against specific risks that are known to have an adverse effect on crop yields using a burn-rate historical frequency model. For temperatures, these take two forms - degree-day contracts and daily temperatures - and likewise for precipitation we may write contracts for both daily and cumulative precipitation.

The degree-day contracts are based on the models established for the energy industry and are designed to accumulate for any temperatures above or below a benchmark value. As mentioned above, the energy industry considered 65° F to be a useful benchmark value, above which Cooling Degree Days (CDD) are accumulated, and below which Heating Degree Days (HDD) are accumulated even though common sense might dictate that “Cooling” Degree Days be observed in cooler temperatures below 65° F. This distinction originated because temperatures above 65° F are considered to require energy for cooling and below which require energy for heating. In agriculture we define an additional degree day index, the Growing Degree Day index, which accumulates for temperatures above 50° F, although given the flexibility of the methods presented in this paper any benchmark value may be entered.

The mathematical definition of degree day indexes is thus:

$$CDD = \sum_{t=1}^{T} Max[D_t - 65,0]$$

$$HDD = \sum_{t=1}^{T} Max[65 - D_t,0]$$

$$GDD = \sum_{t=1}^{T} Max[D_t - 50,0]$$

Where D_t is the temperature on day t and T is the total number of days in the event in question. The cumulative degree-day index is then compared against a strike value, which operates similar to an option contract as both calls and puts may be written.

The generalized payout functions are similar and differ only in terms of the benchmark value and direction of accumulation. The payout function for CDD is given by:

$$Payout[CDD] = \Theta \int Max(DD_T - 65,0) f(DD) \quad dDD$$

Where Θ is the payout multiplication parameter and *f(DD)* is the density function of the statistical distribution of degree days. (Full discussion on Θ is in the Payout Options section.) For *f(DD)* we may insert several different types of function. For this thesis, we use a burn rate analysis based on historical frequencies, but other researchers have used a log-normal distribution (Cao and Wei 1999) or ().

For historical burn-rate analysis we may rewrite this payout function not as an integral but as two nested addition functions.

$$Payout[CDD] = \Theta \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} Max[D_{t,n} - 65,0]$$

Where N is the number of years for which we have data, and $D_{t,n}$ is the daily temperature value for day t in year n. This will give us the average number of degree days for the given date and year range at a particular station.

For daily temperature contracts, instead of an accumulation of degree days we define a specific event risk each period for which the temperature observation is above or below a certain threshold. For example, we might consider a heat risk event as temperatures above X degrees for Y days, where X is a relatively high temperature like 85° F and Y is a period which is determined to result in crop damage for heat. We calculate the number of non-overlapping events within the date range for which these criteria are met and multiply the payout amount by that number, up until a maximum set by the user. The final payout is determined by the average number of observed risk events across the entire range of years.

For example, if we are looking at 14-day heat waves, only two events are possible in the month of June, since the events are non-overlapping. Each year will have either 0, 1, or 2 observed events, and the average of this number will determine the actuarially fair premium when multiplied by the payout parameter Θ.

Contract Design – Precipitation Contracts

Daily rainfall contracts are identical to the daily temperature payouts in that specific events are defined by a comparison of daily values. The difference is one of scale, in that the index is not in degrees but inches.

For example, a drought might not be defined as a period without any precipitation at all, but under a small threshold amount for each day. Using a daily rainfall contract, we might define a drought as X consecutive days with rainfall below Y inches, where Y is a value like 0.05" and X is a value assigned to reflect the number of days beyond which crops would suffer from an absence of moisture.

Cumulative rainfall contracts share some similarities with the degree-day contracts, in that they are both accumulating values across a date range. However, cumulative rainfall differs in that multiple events may be selected, just as in the daily-type contracts, whereas the degree-day contracts are by default across the entire date range. If the insuree desired a contract in the cumulative rainfall mode similar to the daily rainfall mentioned previously, the X entered would be the total rainfall across a date range, regardless of the daily values. Just as in the daily measurements, these events are non-overlapping and only a certain number could happen in any given year. For example, we might define a drought as less than X" *total* across Y days.

Payout Options

The contract options allow for some flexibility in payout amounts. For the daily temperature and rainfall contracts, the payoff is calculated for each observed event, and some differentiation in the pricing is achieved by allowing for multiple events. In other words, the severity of a year can be assessed by the number of risk events occurring and insurance premiums can be adjusted accordingly.

However, for the degree-day, and to a lesser extent the cumulative rainfall, we cannot use this method because the index accumulates across the entire date range. To price the premium using this method would result in a series of binary payments in which the criteria was either fulfilled or wasn't. The solution to this is to offer a "Unit" payout which pays out based on the severity of the season in question. For severe results

For example, let's say we set the strike value in a CDD contract to be 100, but observe 150 degree days in a given period. Under the "Lump Sum" option, the payout would be a straight sum, but for the "Unit" payout it would be multiplied by 150/100 = 1.5 to arrive at the final value. In this way we may adjust the payout amounts to reflect the severity of a season. An illustration of this may be found in Figure 5 above, which also has a ceiling above which the payout does not vary, as it is assumed that any rainfall below 50 mm will result in total crop failure.

Commercial Purveyors

For real-world examples, MSI Guaranteed Weather LLC (http://www.guaranteedweather.com/), a commercial purveyor of weather index insurance, provides functionality similar to Weather Wizard, but offers many examples for heat and precipitation products for industries including agriculture, construction, energy, health, and leisure. Some sample weather products include:

- Insurance for barley growers for excessive precipitation with payoffs for each three consecutive days with total precipitation >= 0.35 inches, for up to nine events.
- A policy designed to insure against excessively cold days which interrupt construction projects. Payoff of $50,000 for each day in which the low temperature is <= 10° F in excess of 10 days in any given year.
- A policy for a theme park that wanted to insure against lost revenue for rainy days. For any day in excess of 8 days in which the rainfall was more than 3mm, the park was paid $25,000.

If risk conditions may be precisely defined, it is very easy to price these insurance contracts from the data, but therein lies the difficulty, as it may not always be said with certainty that the observed historical frequency of any given event will allow for accurate pricing of an insurance policy.

Indeed, the underlying weather index is not a simple reflection of downside risk. The difference between the payoff of the insurance contract and the underlying risk is known as basis risk, and is a fundamental problem. Weather index insurance substitutes the problems of adverse selection and moral hazard with the problem of basis risk, and any effort to implement weather index insurance is an effort to systematically reduce basis risk.

Basis risk may take two basic forms in the context of weather index insurance. First, "local" basis risk refers to the phenomenon by which observed weather variables do not correspond strongly with yield losses. We must recognize that weather is undoubtedly a factor in crop production, but must be considered simultaneously with other, often undetectable factors. Furthermore, stations with a dearth of useable data will experience difficulties in accurate pricing.

The second type of basis risk is referred to as "geographical" basis risk, and refers to the spatial relationships of risk in a geographic area and the variance introduced at increasing distances from locations where the weather observations are known quantities.

Adjusting the Specific Event Paradigm for Joint Risk Events

As valuable as the study of single event risks is, we also want to consider risks that happen simultaneously, especially if they have effects above and beyond those caused by their solitary presence – a classic example of a joint risk scenario is a combined heat/drought event. It is easy to tabulate the number of years for each individual risk event (e.g. both heat *and* drought) and arrive at two separate premiums, but to do so would ignore the years with combined effects.

To calculate the joint risk premium for a given event, the risk event is only considered to be present in years in which all risk events occurred, regardless of the number of times they occurred. This is because it is impossible, as a general rule, to compare risk events of different types without further inquiry into the nature of joint risk. This is especially true when considering that the date ranges are variable for each event.

Weather Wizard has been programmed to do just this, and will tabulate the risk but the final output is a percentage of the years in which all risk conditions were present. It is that percentage that we use to calculate the insurance premiums in Chapter 4.

Chapter 3 - An Internet Based Tool for Weather Risk Management

Introduction

The pricing of weather insurance, and more generally the enumeration of weather risk, is not an easy task. Data are not so easily accessible, and assessing the data in terms of all of the possibilities of risk is burdensome (Campbell and Diebold 2003, Changnon and Changnon 1990). Furthermore the numbers of possibilities are virtually endless, and what might be an insurable weather risk at one location may not be insurable at another. It is for this reason that academic research has focused so heavily on the general rules of probability that govern loss and weather insurance/derivative premiums rather than making broad generalized statements about application (Turvey 2005).

There are two gaps in the literature. The first is rudimentary. The literature on weather risk management as cited above focuses more on insurability than on how weather interacts with agricultural production and farm households as a source of risk. The idea that weather and crop yields represent covariate risks is taken as given and the effects of climate and weather variance on crop production has long been understood (Bardsley, Abey, and Davenport, 1984; Changnon, 2005 ; Huff and Neill, 1982; Runge, 1968). A more complete understanding of how covariate risks evolve in a production system, even at the conceptual level, can provide invaluable insights to the practitioner and theorist. In this paper we present such a model. It is not a precise model, nor are we in a position to empirically validate the model, but it does provide the requisite insight to understanding covariate risk and how covariate risks interact with farm livelihoods to create an insurable condition.

The second gap, and the focal point of this paper, is the measurement of weather risk and the insurability of weather risk. Despite recent interest in weather insurance, the idea of insuring weather risk as an alternative to crop insurance is not new (several articles predating 2000 that made such propositions include Changnon and Changnon, 1990; Gautman, Hazell, and Alderman, 1994; Quiggin, 1986; Patrick, 1998 ; Sakurai and Reardon, 1997). Since 2000, a variety of weather insurance models, propositions, theorems, and structures have been proposed, but there is little agreement on how weather risk should be defined or how weather insurance should be priced [Alaton, Djehiche and Stillberger, 2002, Alderman and Haque, 2006, Cao and Wei, 2004, Considine, (undated), Davis, 2001, Dischel, 2002, Geman, 1999, Jewson and Brix, 2005, Leggio, and Lien, 2002, Muller and Grandi, 2000; Nelken, 1999, Richards, Manfredo, and Sanders, 2004, Turvey 2001, 2005, Zeng, 2000]. Applications of weather insurance in North America, Europe and developing economies are varied and include numerous important contributions to a range of issues including agricultural production risk, food security, poverty alleviation, irrigation insurance, intertemporal risks and so on (Alderman and Haque 2006, Hao and Skees 2003, Hazell, Oram and Chaherli 2001, Hazell and Skees 2006, Hess, Richter and Stoppa 2002, Lacoursiere 2002; Leiva and Skees 2005; Mafoua and Turvey 2003, Martin, Barnett and Coble 2001, Muller and Grandi 2000, Skees, Hartell and Hao 2006, Skees, Gober, Varangis et al 2001, Stoppa and Hess 2003, Turvey, Weersink, and Chiang 2006, Vedenov and Barnett 2003, Veeramani, Maynard and Skees 2004).

Part of the problem is that use of the term ‘weather risk’ is far too ubiquitous and agricultural economists seeking agreement on a definition of weather risk will ultimately be disappointed. As will be discussed presently, the term implicitly includes considerations of frequency, intensity, and duration. The gap extends when one asks "what risk?" and expands even further when one tries to determine, evaluate or measure the risk. It is no easy task and perhaps too much of the academics' energy is used on measuring the risk rather than defining the risk and applying the risk. This is at the core of this paper. In this paper we describe a web-based application program called Weather Wizard (www.weatherwizard.us) that was developed along the lines of Turvey (2001) for specific event temperature and precipitation risks and Turvey (2005) for degree-day temperature risk. The program accesses heat and precipitation data for all NOAA weather stations (currently available to 2001) in the United States and can be used to investigate weather related risk and calculate insurance for virtually all possible single and multiple specific events.

The main contribution of this research is the outreach tool itself. Weather Wizard can be accessed by researchers, crop insurance specialists, educators and practitioners. In a very short period of time measured in minutes rather than days or weeks, the user can select any location, define a specific event, and enumerate that risk. Furthermore, users can evaluate up to five joint precipitation and temperature risks as well as basis risk for a specific weather event for all weather stations within 50 miles of a specific location.

The paper proceeds as follows. First, we provide a conceptual overview of weather risk in the theory of production. Second, we focus on the meaning of "weather risk" and then we describe in general terms the underlying philosophy of the computer program and the meaning of specific event risk. In the Appendix, the program is illustrated in terms of screen displays and application.

Economics and Weather Risk

The central focus of this paper is the presentation of a web-based computer program designed for the measurement of weather risk. To motivate the need for such a program, this section outlines the relationships between production economics, weather risk and farm livelihoods to show how specific weather events interact as a source of risk and how these risks can be mitigated using weather insurance. We make two assumptions. First we assume that the specific weather event is treated as a stochastic input into the production function and second, livelihood is measured in the context of a whole farm or household production function. We do not assume a stochastic production function that simply adds randomness to a deterministic function. Rather, we assume that the weather event creates randomness in the production coefficients themselves so that marginal productivity is endogenously random. Keeping in mind that any production function will do, we start with a classical form of production:

(1) $$Y\left(x,\bar{\varpi}\right)=\alpha_1\left(\bar{\varpi}\right)+\alpha_2\left(\bar{\varpi}\right)x\text{-}\alpha_3\left(\bar{\varpi}\right)x^2$$

where x is an ordinary input (e.g., fertilizer) , and $\alpha_i\left(\;\right)$ are random coefficients of the production function. If one were to assume that $\alpha_i\left(\omega\right)=\alpha_i+\beta_i\omega+\varepsilon_i$ is a function of some specific weather event ω defined over some (known or unknown) probability distribution function that describes the specific event risk, then the stochastic production function is

(2) $$Y\left(x,\omega\right)=\alpha_1+\beta_1\omega+\left(\alpha_2+\beta_2\omega\right)x-\left(\alpha_3+\beta_3\omega\right)x^2+\varepsilon_1+\varepsilon_2x-\varepsilon_2x^2,$$

with expected production being

(3) $$E[Y,(x,\varpi)]=\alpha_1+\beta_1\varpi+(\alpha_2+\beta_2\varpi)x-(\alpha_3+\beta_3\varpi)x^2$$

Under the independence assumption, yield variance, conditional on weather risk, is defined by

(4) $$\sigma_Y^2=\left(\beta_1^2\sigma_\omega^2+\sigma_{\varepsilon_1}^2\right)+\left(\beta_2^2\sigma_\omega^2+\sigma_{\varepsilon_2}^2\right)x^2+\left(\beta_3^2\sigma_\omega^2+\sigma_{\varepsilon_3}^2\right)x^4.$$

In words, the standard errors of the production coefficients comprise two influences. The first, we argue is the influence of weather risk, and the second is an unrelated risk. It is of course assumed that if weather insurance is to be viable as a risk management tool then the portion of the standard error attributable to weather must be significantly and proportionately higher than the non-systematic risk component. In any case, weather risk influences the production of agricultural products by causing a shift in the location of the production function as well as its slope and shape, and the nature of these risks are contingent on the ex ante choice of x. This choice will be based upon average or expected evolution of crop-specific weather events throughout the growing season. The interaction of ideal weather events with optimum input levels can lead, ex post, to higher yields and marginal productivity, while poor weather interacts to reduce marginal productivity and yields. In other words the production function coefficients are random, and the final yield depends on the specific weather event conditional on the initial deterministic choice of x.

The effect on total productivity due to a change in ω from its mean is

(5) $$\frac{\partial Y(x,\varpi)}{\partial \omega} = \frac{\partial \alpha_1(\omega)}{\partial \omega} + \frac{\partial \alpha_1(\omega)}{\partial \omega} x - \frac{\partial \alpha_1(\omega)}{\partial \omega} x^2 .$$

Because ω is a random variable the ex post distribution of crop yields would appear as:

(6) $$Y(\omega \mid x) = \int_u^l Y(\omega) f(\omega) d\omega .$$

The marginal product function of $Y(x,\varpi)$ is given by

(7) $$\frac{\partial Y(x,\varpi)}{\partial x} = \alpha_2(\varpi) - 2\alpha_3(\varpi) x$$

and basing ex ante input choice on the expected value of ω, the expected yield maximizing choice of input is $x^* = \frac{\alpha_2(\omega)}{2\alpha_3(\omega)}$. In reality the actual marginal productivity of x is a stochastic function.

(8) $$\frac{\partial^2 Y\left(x,\bar{\omega}\right)}{\partial x \partial \omega} = \frac{\partial \alpha_2\left(\omega\right)}{\partial \omega} - 2\frac{\partial \alpha_3\left(\omega\right)}{\partial \omega}x\,,$$

which can also be expressed as a conditional marginal product function

(9) $$\text{MPP}\left(\omega \mid x^*\right) \;= \int_{\text{u}}^{1} \frac{\partial Y\left(\omega \mid x^*\right)}{\partial \omega} f\left(\omega\right) d\omega\,.$$

In other words, weather is not simply a passive actor in agricultural productivity, but can change not even the total productivity by shifting the production function up or down, but also the marginal productivity. Nor is it a simple distribution about some level of expected yields, but a factor that can change the shape of the production function throughout the range of x. The efficiency of production is also at risk. Given a prior choice of x and no bounds on $\alpha_i\left(\omega\right)$, $\frac{\partial^2 Y\left(x,\bar{\omega}\right)}{\partial x \partial \omega} <=> 0$ such that ex post production relative to input choice can exhibit increasing, constant or diminishing returns to scale, even though in the deterministic model, only diminishing marginal productivity would be observed.

We now define a weather contingent livelihood function that can be thought of as a stochastic household production function. Its general form is given by

(10) $$H\left(Y\left(\omega\right),\omega\right) = \int_l^u h\left(Y\left(\omega\right),\omega\right) f\left(\omega\right) d\omega\,.$$

Weather risk enters the livelihood function in two ways. First, as discussed above, agricultural productivity is affected directly by weather risk, but other aspects of livelihood can also be affected. For example, if the farm is financially leveraged, short on working capital or requires investment, liquidity shortfalls from adverse weather events can have economic impacts beyond production. Thus the more flexible form of weather risk management is not necessarily tied to agricultural productivity, but household livelihood. From this we can extract the coverage for specific event weather by extracting from $H(\omega)$ the value for ω that satisfies a minimal livelihood level $\hat{H}(\omega^*)$, $\omega^* = \hat{H}^{-1}(\omega)$. Therefore, a downside weather risk policy will be established according to

$$(11) \qquad \mathrm{E}\left\{\mathrm{Max}\left[\hat{H} - H, 0\right]\right\} = \psi \mathrm{E}\left\{\mathrm{Max}\left[\omega^* - \omega, 0\right]\right\},$$

where ψ converts units of weather into units of currency. A convenient measure is $\psi = \frac{\hat{H}}{\omega^*}$.

It is this interaction between production and farm household well-being that motivates weather risk as an area of study and makes weather insurance useful. However, the actual measurement of weather risk is not easily accomplished. The characteristics of weather risk are discussed in the next section and the tool developed to measure weather risk and weather risk insurance follows.

Frequency, Duration and Intensity of Specific Weather Events

The preceding discussion uses the term "weather risk" in a very general way. It is in fact more complex than a simple definition of a random variable as described. The intent above was to provide a conceptual basis for the measurement of risks that follow. For purposes of this paper and the description of Weather Wizard, we will use for determining the expectation of loss the working definition that a specific event risk is uniquely defined at any location by the functional relationship between duration, frequency, and intensity. Duration is a definition in time ranging from a day, week, month, year or more or less. The model additionally uses the concept of multiple events, which infers a second dimension of time. The first dimension therefore measures the period over which the weather event is to be investigated while the second dimension is a time frame within that period. For example, duration could be measured by any non-overlapping 21 day period between June 1 and August 31. There is a possibility of four non-overlapping events. If it were measured on a 7-day basis, there could be as many as 12 non-overlapping events.

Frequency measures the probability scale defined in terms of the frequency that the event occurs over the specified duration. Frequency here can be based on historical fact (often referred to as the burn rate) or by a defined distribution (e.g., an assumption of log normality).

Intensity is a measure of scale and refers to the quality or condition under investigation and thus requires a point of reference from which quality can be measured and a directional indicator by which condition can be measured. The former will usually be measured by a quantitative criterion such as rainfall or temperature, and the condition is normally defined by whether the actual quantity is above or below the point of reference.

But the terms in their totality must remain flexible. For example a degree-day derivative product is normally defined for a single event in which the event length equals the period over which the product is being measured. Extreme heat or heat waves regarded as a sequential number of days over which daily temperatures exceed a criterion can be defined as multiple events. Likewise, precipitation events based on daily or cumulative precipitation can be multiple or single events and so on.

Care must also be taken in establishing the criteria. Specificity is important. For example we do not in any of our models facilitate insurance or risk management in terms of averages because averages, unto themselves are meaningless. Specific events as we have defined them are based wholly on the sequencing and timing of weather patterns for which full information on the frequency, duration and intensity is required.

The final element is loss value. Unlike crop insurance for which a measured loss can be ascertained by the actual weight of crop harvested times a price, the loss value from yield-independent weather risk is less obvious. By “yield-independent” we mean that any payout from weather insurance is provided based on recognized weather measurements at specific weather stations rather than yield loss. It is of course assumed that there is some a priori recognition that the weather event will be highly correlated with yield loss and that the loss value can be estimated or approximated so that volumetric loss is approximated more or less. This might allow for some speculation on the part of the insured but such speculation does not constitute moral hazard or adverse selection as it is normally construed in the insurance literature, since the premium calculated is actuarially consistent with the weather event. Nonetheless, it serves little purpose to even consider specific events near the average since such insurance will ultimately be expensive and largely uncorrelated with yield loss. Rather, weather insurance should focus on events of the extreme for which, at least within the realm of memoried probability, would most surely result in volumetric and economic loss. For example, it makes little sense for an insured to select a contract insuring against a heat wave based on daily high temperatures in excess of 75° F when loss does not occur until temperatures exceed 90° F; or insuring against less than 1” of cumulative rain over 7 days when it is known that the crop can withstand 21 days with no or little rain.

On this basis we use two dollar-valued measurements. The first is a lump sum or binary payout which simply pays an agreed sum if the event occurs (regardless of intensity) and zero otherwise. The second is a unit payout, similar to options payouts or crop insurance payments in which the payout for each event increases linearly with intensity. The binary option is simple and convenient and is most applicable when the event itself, rather than the intensity of the event is what causes risk. For example, it matters not whether a frost event is measured at 31° F or 20° F, the damage is still done, or if it rains less than 2” in 21 days, irrigation costs will still be incurred whether rainfall is 0.5” or 1.99”. The unit payout is most useful when volumetric losses are known to increase with intensity - for example, if crop losses increase proportionately (or approximately so) as crop heat units fall below or rise above the boundaries of normal crop heat units; or losses increase as cumulative rain falls below a stated quantity, and so on.

Assessing Weather Risk and Weather Risk Insurance with Weather Wizard

We provide in the Appendix screen shots of the Weather Wizard program. In this section we provide, as a matter of illustration, heat and precipitation insurance results obtained entirely from Weather Wizard. We use for our example the city of Ardmore, Oklahoma (Carter County), which has continuous daily heat and precipitation data from 1902 to 2001. Perhaps more than this is its location between Oklahoma City and Dallas, Texas, which places it centrally in the areas affected by the Dust Bowl activity of the 1930s, providing thus a historical perspective on extreme weather events that is represented by the data and which will be familiar to most readers. We compare to this weather risk recorded at Cornell University at Ithaca in central New York.

Heat Insurance

Insurance based on heat is far more common in the energy industry than found in agriculture, but for many agricultural commodities extreme heat can cause volumetric decline in yield, quality loss, energy consumption, and livestock death. The events we speak of are not ordinary events but as indicated above, extreme events that persist for extended periods of time.

Table 1: Historical Degree-Day Comparison for Ardmore, OK and Ithaca, NY, June 1-August 31. Degree-Day measures based on temperatures above daily high temperatures ranging from 80° F to 100° F.

Degree-Day Based On Degrees Fahrenheit (F)	Degree Days	Std. Dev.	Maximum	Minimum
			Ardmore, OK	
80° F	1269	246	1909	520
85° F	837	233	1454	344
90° F	458	201	1007	84
95° F	184	137	595	0
100° F	48	57	247	0
			Ithaca, NY	
80° F	218	111	508	26
85° F	67	58	235	2
90° F	13	19	83	0
95° F	1.4	4.23	27	0
100° F	0.14	0.76	6	0

Table 1 provides a summary of degree-days for Ardmore and Ithaca. Recall that degree-days in the energy industry are measured relative to 65° F and corn heat units relative to 50° F, but this need not be viewed as a meaningful economic standard. Heat stress in agriculture does not in most cases occur until temperatures are well in excess of 80° F, so it makes little sense to include temperatures below the stress levels. But stress must also be measured relative to climate. The degree-days measured in Table 1 are obtained by adding together the difference between the (91) daily high temperatures in excess of the degrees identified in the first column. The mean degree-days are provided in column 2, the standard deviation across years in column 3, and the historical maximum and minimums in columns 4 and 5. For the same temperature measures the degree-days are strikingly different between Ardmore and Ithaca. In Ardmore, a southern location, for example the average degree-days based on 90° F is 458 with a standard deviation of 201, but for Ithaca it is only 13 with a standard deviation of 19. Clearly any heat insurance policy designed for Ithaca is not applicable to Ardmore.

Table 2: Degree-Day Heat Insurance Premiums based on 85° F Degree-Days ($1,000/degree)

Ardmore, OK		Ithaca, NY	
Strike	Premium	Strike	Premium
850	89,520	50	30,041
900	70,270	75	20,054
950	53,739	100	13,514
1000	40,307	125	8,518
1050	29,818	150	4,730
1100	21,473	175	2,108
1150	15,224	200	797
1200	9,974	225	135
1250	5,943		
1300	3,339		
1350	1,615		
1400	573		

Weather Wizard in fact was designed with such differences in mind. Weather insurance cannot be applied in an ad hoc fashion, but must be computed at each individual location. The effect is seen in Table 2 which provides premiums for an 85° F degree-day excess heat contract for June 1-August 31 for Ardmore and Ithaca. Not only are insurance strike or coverage levels evaluated at Ithaca irrelevant to the climatic conditions at Ardmore, but the cost differences are also significant. Given the range of degree-days in Table 2 for 85° F it makes little sense to consider insurance that is close to the mean for it is unlikely that economic damage would be significant at that level. In addition to choose a strike of say 1,000 for Ardmore or 100 for Ithaca comes at such a high cost because at these levels some amount of payment will appear in almost every year. It is the extreme events with low probability but high economic loss that matters. In Ardmore considering such insurance at a strike of 1,350 or higher, or in Ithaca 200 or higher, would probably be more sensible.   This discussion also raises the issue of what is an extreme event. Is it a 1 in 100 year event, 1 in 50 year event, or 1 in 10 year event? There is no set answer but Weather Wizard can be used to identify the risks.

Table 3: Multiple event heat-wave frequencies (events per 100 years) based on Daily High Temperatures exceeding 90° F for N Consecutive Days and showing risk differences between Ardmore and Ithaca.

Event length (days)	Premium	0 Events	1 Event	2 Events	3 Events	4 or More events
			Ardmore, OK			
7	7,469	0.00%	1.04%	2.08%	4.17%	92.71%
14	2,729	6.25%	10.42%	26.04%	27.08%	30.21%
21	1,427	16.67%	39.58%	29.17%	13.54%	1.04%
28	823	37.50%	43.55%	17.71%	1.04%	0.00%
35	510	55.21%	38.54%	6.25%	0.00%	0.00%
			Ithaca, NY			
2	1,865	40.50%	16.20%	17.60%	5.40%	20.30%
3	757	60.80%	18.90%	12.20%	1.40%	6.70%
4	324	77.00%	16.20%	4.10%	2.70%	0.00%
5	95	92.00%	6.80%	1.40%	0.00%	0.00%
6	68	93.00%	7.00%	0.00%	0.00%	0.00%
7	27	97.00%	3.00%	0.00%	0.00%	0.00%
8	14	99.00%	1.00%	0.00%	0.00%	0.00%

The use of degree-days as a measure of risk represents a broad seasonal measure of risk. It is only specific to the time frame in question (e.g., June 1-August 31) and represents more or less the intensity of broad temperature risks such as a summer that is hotter than usual or cooler than usual. An alternative approach is to examine specific events. Table 3 presents results for the specific event of a heat wave in which the daily high temperature exceeds 90° F for N consecutive days (the event length). Weather Wizard can also compute risks of multiple events. For example for a 7-day heat wave there are 13 possible non-overlapping 7-day events, and for a 35-day heat wave there are only 2. The results in Table 3 are based on the maximum possible events. Again, one must rethink what constitutes a heat wave. A 7-day event will occur at least once a year in Ardmore, Oklahoma and in fact there is a 92.71% chance of four or more such events, but a 7-day event in Ithaca NY is extremely rare occurring only 3 of every 100 years. Likewise a 9-day heat wave has never occurred in Ithaca (given the data available) but in Ardmore in 38 of every 100 years there is a possibility that daily high temperatures will exceed 90° F for 35 straight days and in 6 of every 100 years this could occur twice.

When considering weather insurance one must also consider how agriculture has adapted to the climates in each region. Irrigated cotton and wheat in southern Oklahoma is an agricultural adaptation to that region's climate as much as dairy, orchards, grapes for vines, corn and soybeans are an adaptive response to the climate of the northeast. Furthermore, grain and oilseed hybrids have been developed for specific heat units that are adaptive to a region's climate. It is when climate exceeds the bounds of adaptation that weather insurance is most valuable.

Precipitation Insurance

Table 4: Seasonal Cumulative Precipitation Insurance Premiums, 91 Days June 1 and August 31, for Lump-Sum and Unit Payouts ($1,000/inch)

	Ardmore, OK			**Ithaca, NY**		
Average	9.08"			10.74"		
Std Dev	4.57"			2.77"		
Less Than	Lump Sum	Unit Payout	Frequency	Lump Sum	Unit Payout	Frequency
2"	10.1	0.3	0.0101	0	0	0
3"	50.51	26.26	0.0505	0	0	0
4"	101.01	97.37	0.101	0	0	0
5"	212.12	246.77	0.2121	0	0	0
6"	303.03	487.78	0.303	13.51	2.97	0.0135
7"	383.84	838.48	0.3838	81.08	50.81	0.0811
8"	474.75	1276.06	0.4747	162.16	167.3	0.1622
9"	575.76	1798.28	0.5758	310.81	408.51	0.3108

precipitation. Again regional adaptability and differences need to be considered. Table 4 illustrates premiums and risk for cumulative rainfall between June 1 and August 31. This is a 91-day event and is the most basic of precipitation insurance contracts. There are two insurance calculations in Table 4. The first is that if the event happens then a $1,000 payment would be made. The second is based on a unit payout which means that a payment is made on the positive difference between the coverage level and actual cumulative rainfall only. For this reason the lump-sum insurance is more expensive at lower precipitation levels and less expensive at higher precipitation levels.

In Ardmore the cumulative rainfall is 9.08” with a standard deviation of 4.57”, while in Ithaca the average cumulative rainfall is 10.74” with a standard deviation of 2.77”. Clearly rainfall is less prevalent and more variable in southern Oklahoma than central New York. Furthermore, southern Oklahoma is far more drought prone than

Central New York with a 1 in 100 year event of less than 2" of rain over the 91-day period, and 30.3% chance of cumulative rain falling below 5". In contrast the data available for Ithaca indicates that in no year did cumulative rainfall in Ithaca fall below 5". In Ardmore there is a 57.58% chance of less than 9" of rainfall but in Ithaca the chance is only 31.08%. For this reason the insurance costs for drought insurance is much higher in Ardmore than Ithaca, and again one must consider the practicality of offering drought insurance in an area prone to drought.

Table 5: Multiple Event Cumulative Rainfall Insurance ($1,000 lump sum or $1,000/inch

	Cumulative Rainfall					
Event Length (Days)	**0.25"**	**0.50"**	**0.75"**	**1.00"**	**1.50"**	**2.0"**
			Ardmore, OK / Unit Payout			
7	1584	3369	5341	7380	11809	16505
14	504	1141	1824	2626	4430	6361
21	224	521	876	1200	2162	3071
28	104	239	418	609	1064	1588
35	63	150	247	362	633	952
42	23	57	96	186	346	589
			Ardmore, OK / Lump Sum Payment			
7	7828	8565	9182	9626	10111	10424
14	2798	3293	3747	4162	4566	4949
21	1354	1687	1990	2222	2566	2828
28	636	869	1080	1313	1485	1808
35	384	525	687	798	1050	1253
42	162	232	354	475	707	879
			Ithaca, NY / Unit Payout			
7	784	2061	3718	5712	10501	16124
14	101	319	713	1051	2391	4153
21	19.5	64	158	245	663	1304
28	7.3	16	43	67	202	416
35	2.03	6	13	15	57	157
42	2.03	5	9	0.41	22	53
			Ithaca, NY / Lump Sum Payout			
7	5635	7919	9365	10351	11675	12351
14	838	1675	2581	3243	4473	5257
21	162	432	676	1000	1932	2541
28	54	81	203	324	730	1203
35	14	27	54	81	230	486
42	14	14	14	27	95	189

Table 5 provides examples of specific event risks for different risk criteria. The values are premiums based on lump sum and unit payouts as well as the maximum number of possible events. Here the specific event risk is defined by event lengths from 7 to 42 days. Close examination of the results indicate the significance of the timing and sequencing of rainfall in determining insurance premiums for specific event risks. Reading across the rows it is clear that the cost of precipitation insurance will increase as the event criteria increases. Insuring against receiving less than 0.25" in any 21-day period will cost only $104, $636, $19.50, and $162, in comparison to a policy with a 2" requirement costing $3,071, $2,828, $416, and $2,541. This is simply reflecting the fact that it is far less likely that cumulative rainfall will be less than 0.25" than less than 2.0". Looking down each column reflects the temporal risk. It is far more likely that rainfall in any 7-day period will be less than 0.25" than in any 42-day period.

Summary

Space constrains all the possible considerations for weather insurance and weather risk management with Weather Wizard. The degree-day derivative worksheet, for example, was not even presented, but a word on the pricing of degree-day insurance using the Black-Scholes model is warranted. The algorithm underlying the degree-day 'derivative' approach is outlined in Turvey (2005), and in that paper considerable space is dedicated to a reasoned comparison of a number of methods including that proposed by Richards, Manfredo, and Sanders (2004). It is not the final word for sure, for there is still considerable debate on the role of the market price of risk [assumed zero in Turvey (2005)] and the use of equilibrium pricing models in general.

Having said that, the intent of this paper was not to provide the mathematical or structure of weather insurance or derivative pricing but to present a tool that can be used to investigate specific event weather risks and to price the value of mitigating such risk. Not presented in this paper are newer developments to the program that include two new algorithms. The first follows through on the definition of risk. In many circumstances yield loss may not be due to a single event but to joint events. Rust, nematodes, molds, and insect infestations often arise from combined events such as a wet spring followed by a cool summer, or a dry spring followed by a hot summer and so on. Again the risk combinations are specific. As at the time of this writing up to five separate events can be defined and the joint probabilities assessed. We believe that measuring intertemporal covariate risks such as excess heat jointly with rainfall shortfalls by season or event is clearly the next step in designing insurance instruments to manage weather risks.

The second innovation not presented in this paper is the evaluation of basis risk. At the time of writing this particular algorithm is near completion. It too is important. One of the major concerns with weather insurance is the problem of basis risk which refers to the risk differential between a defined location such as a farm, and the point of measurement or weather station. If there is too much variability across space and time then weather insurance may not capture the true intended covariate risk. The Weather Wizard algorithm defines a radius of up to 50 miles around a given location (zip code) and identifies all weather stations within the defined circle. The weather station locations can be viewed using Google Earth. Risk contours emanating from the central location will provide a mapping of the risk. Furthermore, a regression algorithm using the basis difference between the central location and the weather stations as the dependent variable and distance, altitude difference and directional indicators (e.g. NW, NE etc) is included to provide an explanation for the basis risks.

Finally, the emergence of weather risk management through insurance or derivative instruments has given rise to a different perspective on risk and risk management. In production economics the measurement of yield risk defined by mean and variance is no longer standard practice. The impact of risks in the extreme and covariate risk should now be defined by specific events and this is no trivial matter. As illustrated in the heat and precipitation examples at Ardmore, Oklahoma and Ithaca, New York specific event risks are such that between any two locations comparison is useful for academic and policy purposes only. As a practical matter, no common statement of risk between the two locations can reasonably be asserted; the timing and sequencing and frequency of specific weather event risks in Ardmore will have a totally different effect on the production economy than the timing and sequencing and probability of the same specific event risk defined at Ithaca. This new frontier in risk management demands specificity over generalization in order to be meaningful. It is with this in mind that Weather Wizard was developed.

Chapter 4 - The Measurement and Insurability of Plant Disease Risks

Traditional crop insurance is an *ex post* prospect, which is to say that contracts are designed to reimburse agricultural producers for losses incurred. However, traditional insurance products are subject to problems of adverse selection, moral hazard, and prohibitive administrative costs, the majority of which are borne by taxpayers. (Skees 2008) There exists a growing body of literature devoted to the study and analysis of weather derivatives, sometimes called weather index insurance, as it applies to agricultural producers because of the inherent advantages of the pricing model. Not insurance in the strictest sense, hedging risk using an objective measure like weather conditions as a proxy for losses removes subjective judgments in assessing losses, removes the burden of proving losses, and all but eliminates the risk of moral hazard. (Richards et al, 2004; Turvey, 2001, 2005, 2008; Odening et al 2007)

However, previous studies of weather derivatives focus on a single risk event, even though stress events that happen in combination often have negative effects more onerous than stress events happening independently. Some stress events may be considered jointly for accurate compensation of losses, such as heat stress and drought, which have a strong negative effect in correlation (Mittler 2006). One application of this "joint risk" analysis is the pricing of insurance premiums for specific crop disease risks which flourish in observed combinations of temperature and/or rainfall. By deriving the historical frequency of these specific events which are conducive to plant disease infections and growth, we may price premiums for insurance products dependent solely on an objective weather index. It may be possible to insure for joint risk events directly by insuring the underlying weather events that bring about the determinable loss.

Furthermore, because payoffs in the form of weather derivatives are predictive rather than reactive, they may be able to provide a mechanism for additional protection by paying off before the problem has reached a critical stage. For example, risk of Stewart's disease incidence for the growing season is increased by temperate conditions over the winter months preceding it. By carefully studying this risk and providing timely payoffs designed to provide capital for prophylactic insecticide treatments, losses may be mitigated instead of merely insured.

What follows is an attempt to extend existing methodology and pricing of weather derivatives in respect to joint risk events, with examples derived from the literature on plant disease pathologies. We will provide analysis for three plant pathologies (Karnal bunt, silk cut and Stewart's disease), which includes an enumeration for each disease of requisite weather conditions, infection risk, and insurance premium. The weather conditions are gleaned from existing literature in plant pathology and are subject to analysis by the interactive web-based risk management tool first introduced in Turvey and Norton (2008), Weather Wizard, which is used to quantify climatic risk for agricultural producers. Weather Wizard is designed to study the historical frequency of user-entered weather events through exhaustive scrutiny of four weather indexes (three temperature, one precipitation) from 25,000 NOAA weather stations representing all 50 states – an estimated 500 million daily observations in all. It has been designed with the goal of providing the utmost flexibility, so that any weather index may be used at any station where data is available. All of the results presented in this paper may be duplicated by the reader in the "Joint Risk" section of the Weather Wizard website at http://www.weatherwizard.us.

Insurability

If we define ***p*** as the price per bushel of the crop in question, ***Y*** as the normal yield, and ***Y**** as the yield under stress, the equation for loss is:

$$Loss = p\ Max[(Y-Y^*), 0]$$

Calculation of insurance premiums for disease risks must include the following parameters:

f (R,T,t): The frequency of a given weather event with respect to rainfall (R), temperature (T), and time (t).

g(Θ): The probability of infection given favorable weather conditions.

From these elements, we arrive at a calculation of our premium:

$$Premium = g(\Theta)\ f(R,T,t)\ p\ Max[(Y-Y^*), 0]$$

The probability *f (R,T,t)* will be calculated by Weather Wizard from historical weather data . Of paramount importance is the assignment of appropriate parameters for analysis. Unfortunately, we can not always assume that the scientific literature will provide the financial context that we need. Of most concern is developing a meaningful date range at which the crop is vulnerable to disease risk; plant germination and growth vary from year to year and well-defined date ranges can be difficult to come by and by necessity approximations themselves.

Of secondary concern is accurate modeling of the weather criteria presented in the scientific literature. Ideally, scientific literature would use precise financial measurements like degree days or cumulative rainfall; in reality, we often have to "make do" with more imprecise measurements like mean temperatures. Future synergy with plant pathologists on this matter would reap dividends for insurance analysis.

However, in practice the $g(\Theta)$ probability function is most difficult to estimate. Infection rates vary by the hybrid in question and are affected by the weather in natural studies and an artificial rate of inoculation in controlled laboratory studies. Furthermore, a large portion of risk is the existing geographic distribution of the disease, a variable difficult to model at distributed locations without localized knowledge.

Karnal Bunt

Karnal bunt is a disease caused by the fungus *Tilletia indica,* which affects wheat and wheat hybrids. First reported in the Indian state of Karnal in 1931 (from which it borrows its name), Karnal bunt is now found in many countries in Asia and North America, including the United States, in which it was first discovered in 1996. Infection will entail the darkening of the seed, with heavy infection resembling a "canoe or row boat, dark and sunken along the suture line" with accompanying "foul or fishy" odor. (USDA APHIS, 2004) Wheat is only susceptible to Karnal bunt for 2 to 3 weeks of its development period, during which cool, damp conditions must prevail for infection to occur.

Table 6: (After Workneh et al 2008)

Karnal bunt	Variable	Mean	Standard Deviation
Negative (n = 23)	Maximum temperature (° C)	27.17	1.01
	Rainfall amount (mm)	0.29	0.35
Positive (n = 30)	Maximum temperature (° C)	24.22	0.56
	Rainfall amount (mm)	2.34	0.77

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Workneh et al (2008) provide us with our environmental parameters for Karnal bunt infection in Olney and San Saba, Texas. Although the 2-3 week period is contingent on plant maturity and therefore varies from year to year, the researchers provide a series of observations from April 8th to April 25th reproduced in Table 6. The observations are aggregated by Karnal bunt positive and negative years, with a clear pattern shown of cool, damp conditions in the Karnal bunt positive years. To choose environmental parameters for our study, we will consider the statistical distributions of the temperature and rainfall observations. Karnal bunt negative years had a temperature distribution of (25.15° C, 29.19° C) and the relatively cooler Karnal bunt positive years from (23.10° C, 25.34° C); a mean temperature for the period less than 25° C (77° F) can be inferred as high risk. Similarly, the rainfall distribution (in millimeters) for negative years is (-0.41 mm, 0.99 mm) and for positive years (0.80 mm, 3.88 mm); rainfall amounts in excess of 1.00 mm/day (1.8 cm or 0.71" in for the entire period) can be inferred to be high risk. Table 7 provides historical frequency of these environmental conditions: 45.2% of years in Olney and 53.8% of years in San Saba fulfilled these criteria with both mean temperatures below 77° F and rainfall above 0.71”.

Table 7: Frequency of high risk years for Karnal bunt in Olney and San Saba, TX

	Years Pos.	Total Years	Frequency
Olney	19	42	45.20%
San Saba	28	52	53.80%

A few facts about Karnal bunt allow us to price an insurance premium. First of all, Karnal bunt infection does not have a significant effect on yields or kernel size but infected kernels in excess of 3% of yield are said to produce an unpalatable, “fishy” odor in the finished product. (USDA APHIS, 2004) The insurance risk presents itself in the strict federal quarantine that will occur upon positive identification of Karnal bunt in a wheat crop, a condition which will result in total yield loss ($\boldsymbol{Y^*}$ = 0). Second, Karnal bunt is primarily spread through infected seed. (USDA APHIS, 2004) Rush et al (2005) provide us with an assessment of infected fields, and the vast majority of the fields surveyed showed a kernel infection rate of less than 0.02%. (Rush 2005) If we consider 0.02% of seed stock as infected and may potentially transmit the pathogen to future generations, we can assign $g(\Theta) = 0.02$, even though the percentage may be even lower than this. If we estimate a normal yield to be 35 bu/acre, and the price of wheat to be $9/bu, calculating the insurance premiums for Olney and San Saba, TX, is now simple arithmetic and is presented in Table 8.

Table 8: Estimated insurance premiums for Olney and San Saba, TX

	g(Θ)	f(R,T,t)	bu/acre	$/bu	Y	Y*	Premium
Olney	0.02	45.2%	35	$9	$315	0	$2.85
San Saba	0.02	53.8%	35	$9	$315	0	$3.39

The Olney weather station is 243 km (152 miles) due north of the San Saba station, at a virtually identical altitude (360m vs. 363m), and yet insurance premiums for Olney are considerably lower because of the observed incidence of joint risk events. Indeed, analysis reveals a counterintuitive result for those expecting higher temperatures closer to the equator, as mean temperatures in San Saba are approximately 3° C (5° F) cooler than in Olney, which (combined with rainfall) would entail conditions more conducive to Karnal bunt infection. As such, underwriters insuring against a Karnal bunt quarantine in Texas wheat fields would need to adjust premiums accordingly.

Silk cut (And The Need For Clarity)

Fusarium moniliforme is a fungal pathogen which causes a condition called "silk cut" in affected maize ears and is has also been observed infecting other small grain cereals such as wheat, sorghum, and pearl millet. It is known to fill the gaps between kernels on the maize ear, and presents itself with lateral splits around the embryo of the infected kernel, leading to discoloration and a loss of kernel integrity. (Odvody et al 1997) A *Fusarium* strain was responsible for direct yield losses of over 30 percent in Minnesota in 1993. (Ruckenbauer et al 2001) More seriously, some strains of *Fusarium moniliforme* produce a mycotoxin which has been linked to cancer and can cause fatal diseases in livestock. (Munkvold and Carlton, 1997)

Odvody et al (1997) state the following:

"<u>High air temperatures</u>, usually with attendant <u>low soil moisture</u> and high soil temperatures, were common during crop maturation in 1993, as they were in previous years when silk cut incidence was readily detected in vulnerable hybrids.

Beginning at silking in 1993 (23 May) the occurrence of air temperatures of 30°C or higher at both sites abruptly increased from <10 h per week to >40 h per *week (4 weeks) and again abruptly increased to >70 h per week (6 weeks) until maturity in most hybrids at both sites (1 August, kernel moistures <=14%). Air temperatures>=35°C occurred for over 20 h per week during the last 2 weeks prior to maturity."* [1]

Table 9: Prevailing weather conditions for Corpus Christi, TX

	CDD (Benchmark = 70 F)	Rainfall (in.)
Mean	1,539.08	6.17
Std Dev	104.66	4.35
Maximum	1,808.00	17.39
Minimum	1,254.00	0.19
1993	1,340.00	16.47
Std Dev from Mean		2.37

This example highlights a common problem of disease inference: the language of science does not always readily translate into the language of economics and finance. In other words, the specifications are very precise, but not of the nature that we can use. Large-scale analysis of hourly observations is impractical: data from the NOAA does contain information on the hour in which it was collected, but precise hourly measurements across a growing season are currently not available. Even if they were, the costs of computer memory and processing power of hourly observations for 25,000 stations over the last 50-100 years would render any analysis unwieldy, to say the least. Also mentioned are two metrics that are no doubt very important for

[1] However, this is directly contradicted by the weather data that we have on record for the Corpus Christi Airport. Table 4 indicates that heat events (measured in Cooling Degree Days) were at the far end of normalcy at 1.90 standard deviations below the mean, while rainfall measured in cumulative inches for the period is 2.37 standard deviations above the mean. In any case, the year of 1993 could only be considered cool and damp compared to other years on record, not hot and dry.
The most plausible explanation is that some sort of simple error was made in transcribing which year was in question, but whatever the reason, it is impossible to model environmental conditions for this disease risk given recorded weather conditions in 1993.

ecological study, kernel moisture and soil temperatures, but which are useless to us without a reliable conversion method or different approach (such as the biological models of insect population presented as "bug options" by Richards et al (2005)). This paper was written for an audience with different goals than ours and is very typical of the scientific literature.

Given these difficulties, we model for risks as closely as we possibly can. If we know that silk cut is most prevalent in years with high temperatures and low soil moisture, we can construct a simple model based on historical weather conditions. The Odvody study quoted above describes weather conditions between May 23rd and August 1st; for this period, mean Cooling Degree Days (benchmark 70° F) are 1539.08 and mean cumulative rainfall is 6.17". Of course, we are analyzing extreme heat and precipitation events, which for the purposes of this example we can consider to be an excess of one standard deviation in the appropriate direction – a joint risk event with CDD in excess of 1643.74 for heat stress and cumulative rainfall below 1.82" for precipitation stress. When they happen jointly, we might consider that a growing season to be high risk for silk cut infection, which happened in 5 of 52 years (9.6%) in Corpus Christi, TX.

If we accept a figure mentioned previously for a yield loss of 30%, the only parameter left to estimate is the $g(\Theta)$ infection probability function. Munkvold and Desjardins (1997) note that in maize samples in the U.S. from 1988-1995 between 11% and 96% of kernels were infected with *Fusarium moniliforme*. Presumably, the only major variation from year to year was weather conditions, and that in favorable conditions *Fusarium* colonization approaches 100 percent. ($g(\Theta)$= 1)

Using figures of $7/bu for the market price of maize and 140 bu/acre for normal yield, we arrive at a Y of $980/acre. Potential yield loss due to silk cut is 30%

of that, or $294/acre. Favorable conditions were recorded in 9.6% of years, so we arrive at a premium of $28.22/acre for silk cut disease.

Stewart's disease

Stewart's disease (*Panotea stewartii*), also called Stewart's wilt, is a bacterial disease that affects maize and maize hybrids. The primary disease vector for the pathogen is the corn flea beetle, which provides a habitat suitable to survive harsh winters in its digestive tract. Winters that are warm enough to allow large numbers of beetles to survive provide high risk for Stewart's disease in the following growing season.

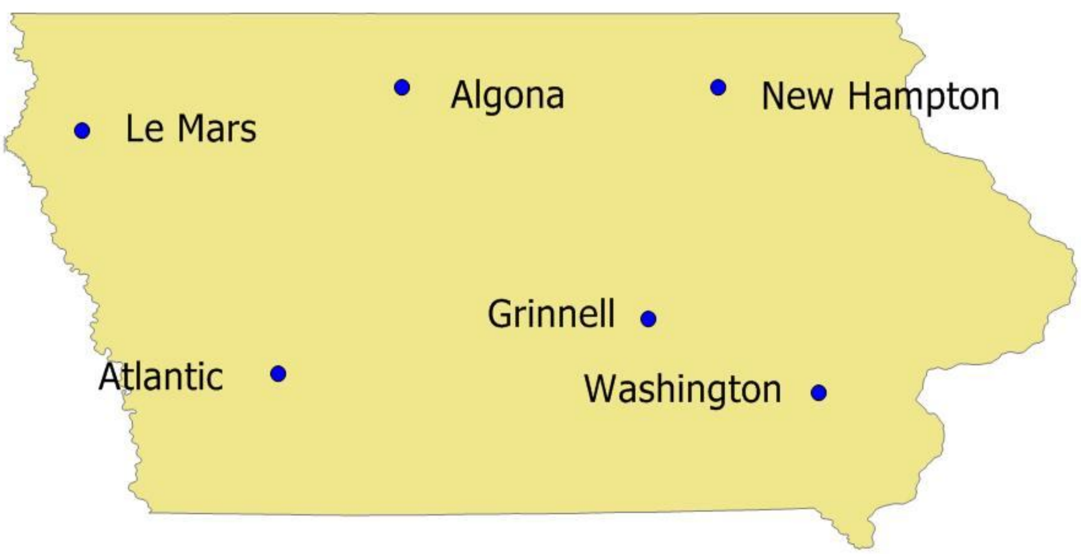

Figure 6: Sites in Iowa selected for study.

The idea of insuring insect risk using derivative products was first presented by the "bug options" of Richards et al (2005). Here, the authors use pest population modeling with a payout on the population density directly. However, they suggest in concluding that weather insurance could be used to offset economic losses from pest infestations. Stewart's disease is a prime example of how such insurance can work.

The traditional model for predicting Stewart's disease is the Stevens-Boewe model proposed in 1934, which assigns risk based on the number of winter months (December to February) that have a mean temperature above 27° F. However, a model proposed by Nutter Jr. et al (2002) and critiqued by Esker et al (2006), notes that the model is more accurate when using temperatures of 24° F instead of 27° F.

We model this in Weather Wizard with a joint risk study with three criteria: one for each month December-February, set to true when mean monthly temperatures are above 24° F. Although the literature provides a sliding scale of risk based on the number of months above that temperature, we are merely concerned with the years labeled "high risk" in which all three criteria are fulfilled (i.e. all three months had mean temperatures above 24° F).

Because Nutter Jr. et al (2002) provides a statewide survey in Iowa instead of a locally focused study, sites were chosen across the state to simulate insurance premiums in those areas. Six sites were chosen in Iowa in distributed locations around the state, as illustrated in Figure 6. Sites with the most data were chosen, with observations going back to 1902 in some cases. The results of the joint risk analysis are presented in Table 10, with criteria successfully fulfilled anywhere from 4.1% to 36.1% of the years studied. Risk for Stewart's disease is shown to be greater in the southern part of the state where warmer temperatures predominate.

Table 10: Frequency of high risk years at selected sites in Iowa

Station	**Positive Years**	**Total Years**	**Frequency**
Washington	31	98	31.60%
Atlantic	18	93	19.40%
Le Mars	13	97	13.40%
Grinnell	11	83	13.30%
Algona	5	95	5.30%
New Hampton	4	97	4.10%

These results are somewhat contradictory to the Illinois study of Woodward and Garcia (2008) who find that basis risk for heat is insignificant when measured against yield loss. As can be seen in the Figure 6, one should be careful not to generalize on the specifics of disease risk. Basis variability, is, or at least can be, very significant when it comes to specific disease risks or as Berg and Schmitz (2008) note when there is an imperfect relationship between the weather index and the biological production process.

Table 11 contains a list of premiums calculated for the chosen sites from Iowa. Four examples for each site were done with an estimated bushel price of $7 and 140 bu/acre to arrive at Y = $980/acre. The yield loss due to Stewart's disease was estimated at 10% (Y^* = $882) for sweet corn and 100% (Y^* = $0) for seed corn (which cannot be sold on the export market). (Esker 2001) Two infection probabilities ($g(\Theta)$) of 17.4% ("low") and 79.5% ("high") were used to illustrate the economic impact of using hybrids with varying degrees of resistance (from 1999 data of Michener et al 2003).

Table 11: Estimated premiums for different breeds of corn

	Risk	Sweet/Low	Sweet/High	Seed/Low	Seed/High
Washington	31.60%	$5.39	$24.62	$53.88	$246.20
Atlantic	19.40%	$3.31	$15.11	$33.08	$151.15
Le Mars	13.40%	$2.28	$10.44	$22.85	$104.40
Grinnell	13.30%	$2.27	$10.36	$22.68	$103.62
Algona	5.30%	$0.90	$4.13	$9.04	$41.29
New Hampton	4.10%	$0.70	$3.19	$6.99	$31.94

Conclusions

The majority of crop diseases, pest infestations, and stress originate with specific weather events, alone or in combination. We have presented here a prescription for insuring specific disease risks given characteristics of infection probability, yield loss, and the historical frequency of the necessary combination of environmental conditions needed for pathogen growth. The ideas presented in this paper are sufficiently general, and the analytical tool (Weather Wizard) is sufficiently flexible to enable a more thorough analysis of weather risks in combination by future researchers. There are many hurdles to clear before we can fully harness the power of the concepts presented in this paper, but the many advantages of weather index insurance as a proxy for losses should reward those with the dedication to making them a financial reality. At the very least, this paper serves to demonstrate just one facet of the vast potential of weather index insurance as a risk management tool.

Finally, would farmers be willing to pay for insurance with such specificity as presented here? Musshoff et al (2008) conclude, but in a somewhat different context, that farmers do/will show a willingness to pay for weather insurance and add that the willingness to pay goes beyond the actuarial price as presented here. Thus farmers would not only pay the fair price for loss, but also any loading that might be added by the insurer. Additionally we might also consider the role of the risk measures here in terms of risk identification by insurers and reinsurers. These institutions do not face single risk as do farmers but a portfolio of risk with sources pooled from many diverse areas. (see Roth et al 2008, Turvey 2005, Miranda et al) Nonetheless, by pinpointing the scientific relationship between weather and plant diseases or insect infestations and identifying spatial risk profiling in terms of joint and conditional probabilities, much of the ‘moral hazard’ problems in agricultural insurance can be alleviated.

Chapter 5 – Weather Index Insurance and the Geographic Variability of Risk

While a comparatively large amount of analysis has been expended on the local effects of basis risk, or more precisely the weather/yield relationship, very little analysis has been done about the geographic nature of basis risk, otherwise known as the uncertainty that develops as we increase distance from a known location. To avoid this problem, researchers sometimes base research at sites with constant elevation (Richards, Manfredo, and Sanders 2004) and conduct projects only within a small geographic radius (such as the World Bank project in Malawi.) Some researchers have even suggested that farmers could hedge risk by purchasing a portfolio of weather derivatives for established cities the CME exchange (Woodward and Garcia 2008).

Even if we had perfect understanding of how to price insurance premiums at a given location, we would not be able to say with certainty how that risk changes through space or how to price premiums at geographically varied locations. A more fundamental approach is needed and this paper describes the search for a general principle whereby risk could be accurately predicted by simple, widely available geographic variables. By understanding the nature of how risk changes through space, we may assess the accuracy of insurance policies written at discrete locations and arrive at strategies for wider use of weather index insurance.

Traditional GIS methods of spatial interpolation like inverse distance weighting are ill-fitting for several reasons. The insurance payout is a function of temperature, but spatial interpolation methods bias the variability, and it is the variability that as insurers we are most concerned with. Second, it is not so much the geographic or spatial relationships that are of interest, but the geographic or spatial relationships given certain weather conditions. In other words, the mean for a known location is only of value at that location, but we need to analyze the spread of risk in a distributed geographic area as different weather conditions prevailed on a year by year basis. The spatial interpolation method for solving this would presumably be to interpolate a map for each individual year of study and combine them to make a composite. This would provide a measure of risk at each location, but this would not, however, allow us to price payouts for unknown locations given a series of observations in future years.

Table 12: Correlation of average of nearby stations of cumulative weather indexes

Heat	**Base Station**	**Avg. of Surrounding Stations**	**Difference**	**Correlation**
CDD Index (85° F):	68.41	71.51	-4.5%	0.8849
Heat Risk Event (Payout):	$22.37	$27.31	-22.1%	0.7751
Rainfall				
Cumulative Rainfall (in.):	10.65	10.36	2.6%	0.7457
Drought Risk Event (Payout):	$20.95	$22.61	-7.9%	0.6897

For illustration, some summary statistics are presented in Table 12. Listed are the aggregate temperature and rainfall observations for Ithaca, NY for June 1st – August 31st along with the average observation for all stations within a proscribed radius (100 miles for temperatures and 67 miles for rainfall.) The overall averages are similar but of course mean values are of little interest. When we examine the yearly variation as measured by the average correlation between the base station (Ithaca) and every other station, we find that heat is highly correlated but rainfall less so. A familiar pattern is that when we introduce risk events (defined later), the variability increases, not only in the averages but also in the correlation. The information presented here is also for relatively common events over long date ranges; presumably these numbers would weaken if a more specific time frame or risk event were used.

The challenge presented is to improve the accuracy of the yearly correlation. Although it is tempting to view this data as a sterile set of statistics, insurance policies would have profound real-world implications for farmers holding a policy. It is crucial to accurately reimburse them in a year when they face actual losses. By taking the payout schedule for all stations and adjusting for geographic variables, we can potentially price insurance contracts for any given point on the map. Because of the vast number of stations located around the country, our hopeful result is a simple equation in which we can build upon this simple methodology and adjust for the differences in distance, altitude, and polar coordinates to arrive at a payout for any unknown location.

Defining the geographic area

Weather Wizard is flexible as to the distance of the radius extending from the base station, but there are a few requirements that must be considered for a successful trial. A number of stations are needed to provide contrast, but there are few stations within a short distance (10 miles) of each other.

However, as we increase the radius of the circle, the area of the circle increases exponentially. Barring any obstacles like oceans, as the radius of the circle increases, the number of stations increases exponentially. Because we compare each station against each other in each year, this also dramatically increases the number of comparisons that are made, as given by the following formula:

$$comparisons = \frac{n*(n-1)}{2} * years$$

Where n is the number of stations within the selected geographic radius. The total is subject to missing and incomplete data; many stations have only limited data, and with longer time horizons the potential of missing data within years becomes greater.

Table 13: Number of comparisons in Ithaca, NY for a given number of miles

		Rainfall		
Miles	Stations	Potential Comparisons	Actual Comparisons	
10	2	225	93	41.33%
15	4	750	223	29.73%
20	12	5850	801	13.69%
25	17	11,475	1628	14.19%
30	25	24,375	3,304	13.55%
35	35	47,250	6,921	14.65%
		Heat		
Miles	Stations	Potential Comparisons	Actual Comparisons	
10	2	225	23	10.22%
15	2	225	23	10.22%
20	4	750	105	14.00%
25	6	1575	220	13.97%
30	10	4125	525	12.73%
35	16	10,200	1,366	13.39%

Perhaps in acknowledgement of the periodic, unpredictable nature of rainfall, observation stations are more densely placed and often contain more years of data. It is very likely that temperature observations are placed more sparsely to reflect that temperatures are considered to vary continuously over a geographic area.

The discrepancy in data for the different weather types is very pronounced, but such factors as length of contract and number years selected will also affect the percentages in Table 13. These percentages are somewhat low because of a relatively long date range. A 92-day window is not unreasonable but offers more opportunities for data to be missing. Also, more importantly, very few stations have data continuously to 1926; most stations date to the late 1940s, and it's not uncommon for a station to have as little as one or two years of data for the entire 75 year period. If we selected a shorter contract length (say, 15 days instead of 92) fewer stations would be disqualified for missing data; likewise, if we only considered years after 1949, the percentage of actual comparisons would improve markedly. This discussion is intended to underscore the fact that even though we might define an identical geographic area, there is often a very different spatial distribution of data within that area depending on the parameters we select.

The advantage of this comparison-based model is that it treats all weather stations equally and is able to include otherwise useless data. In this model the data will be compared on a year by year basis, regardless of how many years of data are at a particular station. The weather stations that only have a few years of data help provide contrast for spatial distributions of risk even though it is impossible to accurately price a contract for that station individually.

Also of pertinent interest is what these details entail for selecting a radius to study. As the radius increases, the area of study increases exponentially (according to the area of a circle – πr^2), increasing the number of stations accordingly, which has vast ramifications for the number of potential comparisons according to the equation above. Since Weather Wizard is hosted on a web platform, there are limitations to the amount of data that it can process in a single iteration - selecting a radius requires the user to select a value large enough to offer meaningful results that will also fit within the technical possibilities. For this paper, we are using a radius of 50 miles, which is large enough to allow the inclusion of sufficient stations for both heat and precipitation, but small enough to run properly on the Weather Wizard website.

The Regression Equation

The goal when formulating this regression equation was to try and predict the difference in payouts in any given year between any two locations using simple geographic variables.

$$(P_1 - P_2) = ß_1 \varphi + ß_2 (\alpha_1 - \alpha_2) + ß_3 (\omega_1 - \omega_2) + ß_4 (\lambda_1 - \lambda_2) + ß_0 + \varepsilon$$

Where P_x are payouts, φ is the distance between the two stations, α_x is the altitude at each station, ω_x is the latitude at each station, and λ_x is the absolute value of the longitude of each station (as longitudes in the western hemisphere are traditionally negative.)

This equation is primarily a difference equation, where we are attempting to explain the difference in payouts by the difference in altitude and geographic coordinates. At first blush, it seems as if the φ variable, distance, is ill-suited for inclusion. However, by imposing a condition of $P_1 >= P_2$ we may ensure symmetry between the left and right sides of the equation; only if $(P_1 - P_2)$ is strictly positive will it reflect a potential linear relationship with φ. Furthermore, distance is a trigonometric function of the individual latitude and longitude variables but is highly correlated to neither. This is because it is a joint function of latitude and longitude, and a degree of longitude is not a constant surface measurement. It is more useful to think of the latitude/longitude coordinates as reflecting directionality, and distance as an adjustment for increasing variability at increased distances.

The equation for distance is given thusly:

$$\varphi = R * Cos^{-1}(Sin(\omega_1) * Sin(\omega_2) + Cos(\omega_1) * Cos(\omega_2) * Cos(\lambda_2 - \lambda_1))$$

Where R is a constant reflecting the radius of the sphere we can use to normalize to standard units; the constant for miles is 3963.1.

What we are left with is a description of how each station compares to each other in three-dimensional space, not only in distance (φ) but with x and y coordinates given by the latitude (ω_x) and longitude (λ_x), and z coordinate given by altitude (α_x). The initial hypothesis of these coefficients follows along the lines of common sense. Distance (φ) should be positively correlated in both heat and precipitation, meaning that as distance increases, so do the differences in premiums. For rainfall, the rest of the geographic variables are indeterminate, given that coordinates and/or altitude would seemingly have no effect on the sporadic nature of rainfall. For heat, however, we might expect that altitude and latitude have a negative effect on risk; or, in other words, heat risk is decreased by either an increase in elevation or more northerly locations.

Defining the Risk Events

Choosing an event that is sufficiently general yet meaningful for all sites is difficult, because there is no such thing as generality, as Chapter 3 tells us. A heat event in upstate New York is incomparable to a heat event in a warmer climate. The sheer variation of climates in America requires us to tailor our heat risk events for each station.

To start, evidence indicates that temperatures above 85° F correlate with crop yield losses. (Schlenker and Roberts 2006) Using this as a benchmark, we accumulate a CDD index above 85° F with the mean CDD at the base station serving as the strike value and a sliding payout for values above that. Payouts are calculated at each station for every year data is available. Figure 7 shows the payout schedule for Ithaca, NY, where mean CDD is 68.41.

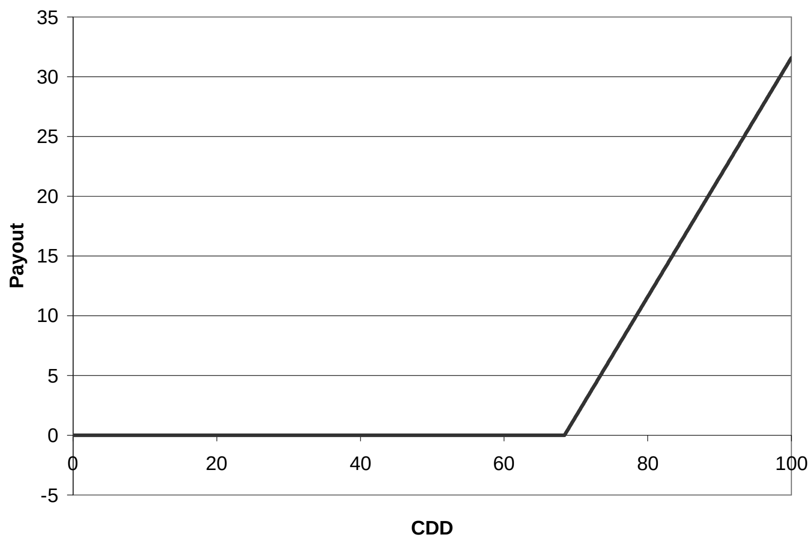

Figure 7: Schedule of payouts for heat risk event

Six weather stations were selected at sites across the country according to quality of data and the absence of major geographic obstacles within 50 miles, such as large bodies of water or international borders. Mean CDD for those six stations vary from 68.41 at Ithaca, NY to 720.63 in Davis, CA and are listed in Table 14.

Table 14: Mean CDD (85° F) at each location

Station	**Bridgeport, NE**	**Bethany, MO**	**Greenville, AL**	**Davis, CA**	**Ithaca, NY**	**Mosquero, NM**
Mean CDD (85 F)	442.13	350.74	603.18	720.63	68.41	282.05

For precipitation, the contract is identical for all sites. We use a drought event of less than .1” of precipitation over any 14 day period. The payoff will occur on a sliding scale with $10 accumulating for each hundredth of an inch less that .1”, to a maximum of $100 per event if no rainfall was recorded. Up to three non-overlapping events are possible, and if more events occur, the variable payoffs are averaged to normalize the payoffs to three events. Figure 8 shows the payoff schedule due to the observed rainfall in any 14-day period, but yearly payoff amounts range from $0 to $300 because of the possibility of multiple events.

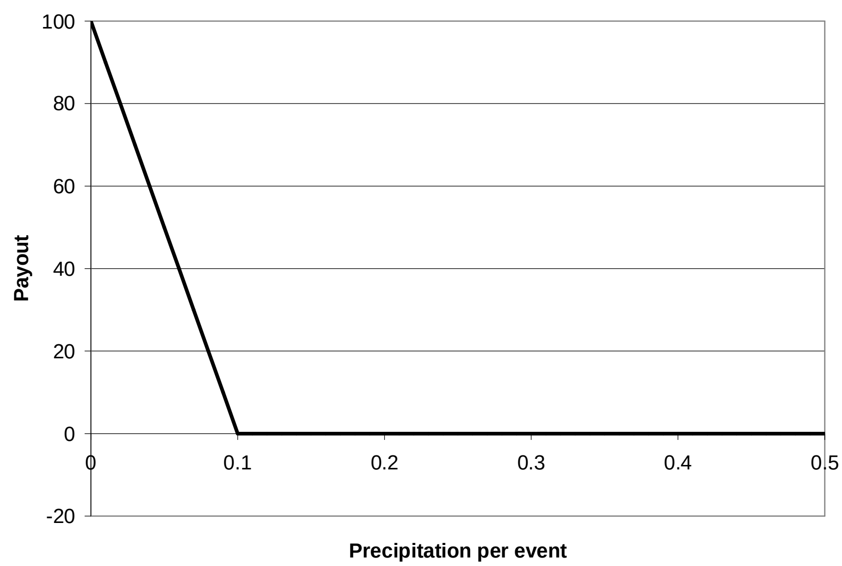

Figure 8: Schedule of payouts for drought risk event

Regression Results

Table 15: Regression results for heat risk event

Station	Bridgeport, NE	Bethany, MO	Greenville, AL	Davis, CA	Ithaca, NY	Mosquero, NM
# of Years	104	75	66	83	74	71
Mean CDD	442.13	350.74	603.18	720.63	68.41	282.05
Stations within 50 miles	19	25	21	44	35	16
N	4300	4417	3052	7255	5953	1831
R^2	0.0103	0.0419	0.0010	0.0157	0.0525	0.4921
Distance	-.215 (-2.22)**	.118 (1.46)	.094 (0.64)	.285 (1.99)**	.035 (1.32)	.394 (1.86)*
Alt. Diff.	-.011 (-2.45)**	-.138 (-8.86)**	-.020 (-1.03)	-.020 (-6.86)**	-.008 (-4.67)**	-.210 (-23.79)**
Lat. Diff.	.428 (0.13)	14.897 (3.03)**	-7.660 (-1.42)	31.278 (5.28)**	-15.926 (-14.41)**	60.886 (3.90)**
Long. Diff.	-9.286 (-2.59)**	15.125 (3.52)**	-2.933 (-0.49)	18.269 (4.33)**	7.852 (9.88)**	84.168 (9.84)**
Constant	52.298 (11.42)**	35.226 (9.48)**	66.999 (8.74)**	80.507 (11.99)**	20.724 (15.17)**	69.946 (8.27)**

The first thing we see when looking at these numbers is that with one exception the R^2 values are abysmal, which is to say that these geographic variables provide a very poor fit for payoff differences. Most of the difference in payoffs is collected in the constant, even though the coefficients are quite often significant, and unpredictably so. Localized conditions can be expected to have effects on the latitude/longitude coefficients, as directionality within different locations might reflect different geographic characteristics.

Table 16: Regression results for precipitation risk event

Station	Bridgeport, NE	Bethany, MO	Greenville, AL	Davis, CA	Ithaca, NY	Mosquero, NM
# of Years	104	75	66	83	74	71
Stations within 50 miles	27	33	41	70	79	35
N	7515	8693	10895	22393	34846	5770
R^2	0.0104	0.0082	0.0131	0.0236	0.0074	0.028
Distance	.074 (2.34)**	.177 (4.94)**	.0001 (0.00)	.049 (8.66)**	.127 (8.91)**	.216 (5.12)**
Alt. Diff.	-.014 (-7.23)**	-.027 (-3.63)**	.017 (4.13)**	-.003 (-18.51)**	.009 (13.36)**	.002 (0.86)
Lat. Diff.	.308 (0.25)	1.821 (0.77)	2.345 (1.84)*	-1.616 (-6.58)**	3.090 (5.26)**	-16.058 (-4.73)**
Long. Diff.	10.054 (7.99)**	10.929 (6.03)**	13.975 (11.21)**	-1.234 (-6.74)**	-.741 (-1.68)*	9.48 (4.26)**
Constant	57.898 (34.48)**	54.71 (31.94)**	63.995 (41.25)**	14.614 (48.68)**	32.353 (43.74)**	66.293 (30.71)**

The two enduring relationships that can be deduced are the effect of altitude on heat risk and the effect of distance on rainfall payoff differences. The coefficient for altitude for the heat risk regressions is consistently negative and significant, which makes sense – we would expect heat risk to decrease as elevation increases. The effect of altitude on rainfall payoffs is unclear, as one might expect – rain perhaps doesn't consider the altitude of the land it's falling onto. The coefficient attached to distance for rainfall is, with one exception, significant and positive, meaning that as distance increases the difference in the payoffs does too. Or, as distance increases, the payoffs become less accurate. We might expect a similar result for heat, as stations further apart produce more differentiated results, but it seems that temperatures vary continuously throughout a geographic region and the directionality measures are often of more interest.

These results may seem to be providing little beyond the very obvious – heat risk decreases with altitude because of lower temperatures at higher elevations; likewise, rainfall correlations decrease with distance because of the unpredictable, periodic nature of rainfall. However, there is little evidence for other seemingly obvious implications, like the relationship between latitude and heat risk – we would expect that heat risk would decrease with increased latitudes, but in fact only one of the six coefficients is negative and significant. In fact, it is somewhat remarkable how little we can say about the relationship between simple geographic variables and differences in downside risk. It has been assumed by many researchers that it would be possible to provide a statistical solution to the problem of geographic basis risk; these results belie the fact that weather may indeed defeat the ability of statistical methods to predict.

Improving the Fit

There are a few transformations that we can do to improve the fit, which is not purely an academic exercise if our goal is to make out-of-sample predictions for unknown locations. The easiest way to improve the fit of the regression is to include dummy variables for the weather stations and years.

The justification for including dummy variables is thus: it is easy to postulate that each station is to some degree idiosyncratic; these dummy variables are intended to catch the effects of nearby lakes or valleys, or anything else that can't be captured by the simple geographic variables that we use. The dummy variables for each year isolate the amount of variability in any given year because the dependent variable is strictly positive. This will account for any years in which payout differences were more pronounced. Both of these dummy variable types may also be included in a pricing algorithm as well, although if we are pricing a premium for an unknown location for which there have never been weather observations, we cannot use the variables which account for station idiosyncrasies.

In addition, the geographic variables don't explain the *difference* in payouts very well, but there is some evidence that the problem is one of scale. The difference equation presented earlier in this paper used (P_1 - P_2) as the dependent variable, which means that it is only very easy algebra to move the P_2 variable to the right side of the equation, where we can fit it with a coefficient. This improves the regression fit markedly but necessitates difficult interpretations of the equation. First, if the coefficient attached to the P_2 variable is significantly different than one, it is difficult to interpret what that means, because P_1 and P_2 are identical in nature and the matter of which one is written first depends only on the ($P_1 >= P_2$) condition. Second, if we're trying to make an out of sample prediction, we can't assume that the P_1 variable will be larger than P_2, which may bias the results.

However, trying to model these effects for predictions at unknown locations becomes problematic. Of course we cannot provide an adjustment for a station idiosyncrasy at an unknown location. Most seriously, if attempting to make a prediction with P_1 on the right side of the equation we cannot guarantee the strict ($P_1 >= P_2$) condition. These methods may have promise, but it is still undetermined whether or not they are statistically viable.

Table 17: Results of transformations in the regression equation

	Original	Incl. Station	Incl. Year	Incl. Station & Year	P1 as Y	All Effects
Rainfall						
DF	34841	34690	34768	34617	34840	34616
R^2	**0.0074**	**0.1788**	**0.1056**	**0.2412**	**0.2644**	**0.4435**
Distance	.127 (8.91)**	.104 (7.05)**	.122 (9.02)**	.102 (7.13)**	.133 (9.37)**	.088 (6.22)**
Alt. Diff.	.009 (13.36)**	-.027 (-4.35)**	.007 (10.50)**	-.0243 (-3.98)**	.009 (12.87)**	-.028 (-4.56)**
Lat. Diff.	3.090 (5.26)**	8.155 (0.81)	3.049 (5.37)**	10.343 (1.06)	2.999 (5.12)**	17.119 (1.76)*
Long. Diff.	-.741 (-1.68)*	12.824 (1.73)*	-.534 (-1.26)	19.805 (2.75)**	-.607 (-1.38)	17.933 (2.50)**
Constant	32.353 (43.74)**	23.671 (8.27)**	25.335 (2.50)**	10.075 (1.03)	30.445 (40.35)**	10.707 (1.11)
P2	--	--	--	--	1.413 (110.38)**	.419 (26.27)**
Heat						
DF	5948	5889	5875	5816	5947	5815
R^2	**0.0525**	**0.2294**	**0.5404**	**0.6134**	**0.6771**	**0.8720**
Distance	.035 (1.32)	.064 (2.21)**	.008 (0.46)	.086 (4.11)**	.037 (1.53)	.070 (3.69)**
Alt. Diff.	-.008 (-4.67)**	-.028 (-3.35)**	-.008 (-6.60)**	.022 (3.59)**	-.0122 (-8.14)**	.035 (6.14)**
Lat. Diff.	-15.926 (-14.41)**	-7.074 (-0.65)	-11.570 (-14.69)**	35.801 (4.55)**	-17.146 (-16.81)**	35.523 (4.97)**
Long. Diff.	7.852 (9.88)**	-24.862 (-2.52)**	5.436 (9.62)**	5.653 (0.78)	7.853 (10.71)**	12.452 (1.88)*
Constant	20.724 (15.17)**	22.048 (5.34)**	8.27 (1.51)	-28.215 (-4.82)**	13.025 (10.16)**	-37.615 (-7.06)**
P2	--	--	--	--	1.124 (110.29)**	.717 (57.20)**

Out of Sample Predictions

Table 18: Out-of-sample predictions

Heat	**Prediction**	**Obs. Average**	**Difference**	**Correlation**
Geo. Variables Only	$25.27	$64.39	-154.8%	-0.4422
With Station & Year Effects	$32.20	$64.39	-100.0%	0.4623
And moving P2 to right side	$67.30	$64.39	4.3%	0.8956
Rainfall				
Geo. Variables Only	$37.34	$64.17	-71.8%	0.4294
With Station & Year Effects	$51.33	$64.17	-25.0%	0.5217
And moving P2 to right side	$66.81	$64.17	4.0%	0.6201

Table 18 shows the results of out-of-sample predictions of payoffs in Ithaca, NY for heat and rainfall including several different types of effects – first with the simple geographic variables, then including the station and year dummy variables, and finally when moving P_2 to the right side of the equation. The predictions with geographic variables are quite bad, but improve with the addition of the station and year effects. The strongest effect is obtained by moving P_2 to the right side of the equations, which may make sense in some ways – the weather observations are the strongest piece of information we have about prevailing conditions in any given year and by taking the difference we often censor that important piece of information. In any case, it must be said that the geographic variables seem to be useful only in the optimization of an already robust distribution – in any successful prediction presented herein, the "heavy lifting" is done by the station, year, and P_2 effects. And in the case of rainfall, this entire exercise has resulted in payouts that are in fact slightly worse than the very simplistic approach taken in Table 12 of simply averaging payouts for each station within 67 miles of Ithaca.

Of course, there are a few caveats that must be mentioned, the first being the difficult mathematical interpretation of moving the P_2 variable to the right side of the equation. Also of note is that this prediction was only performed when Ithaca was the station listed first (i.e. the P_1 variable), the consequence of which is that the payouts are significantly higher (\$64.39 and \$64.17) than the long-term averages as presented in Table 18 (\$20.76 and \$20.87). Whether this has implications for the end results is an important consideration.

Summary

There are two important implications of this paper. The first is that geographic basis risk is a fundamental and persistent problem. Efforts to mitigate risk at diverse locations, even using a portfolio method, will introduce too much variability and best practice is to place a weather station in close proximity to the location of interest. This result is somewhat surprising, in that many researchers have written papers assuming that a solution to the problem of geographic basis risk was eventually forthcoming. However, the search for a general principle failed, which is of interest in and of itself.

The second implication is what this entails for modeling, which is often dependent on spatial variables for interpolating unknown values on a map. What these results show is that traditional spatial interpolation methods that depend on spatial relationships, like inverse distance weighting or kriging, may not be accurate in a local context.

Some researchers are interested in macro-level relationships using satellite imagery or radar data, especially in countries which have little historical data to rely on. What these results show is that even if rainfall can be accurately quantified at one location, the geographic distribution of risk cannot be accurately described and will be prone to error. This is especially true for rainfall, which has the statistically significant, positive coefficient with respect to distance. Further research into predicting risk given known quantities must occur before spatial interpolation methods are used.

Chapter 6 – Conclusions

The study of weather index insurance is still in its formative stages and many technical and theoretical hurdles are yet to be overcome. This thesis starts with weather index insurance at its most basic level and extends the existing literature through the examination of sophisticated pricing methods including joint risk and geographical basis risk.

My goals in writing this thesis were to extend the methodology available for researchers and practitioners of weather index insurance, not only by introducing a publicly available empirical tool like Weather Wizard but also in the methodologies presented in the "joint risk" and "geographic basis risk" chapters. Hopefully the results and methods exhibited in this thesis will be a boon for progress in the area of weather index insurance, which has promising applications in improving the livelihoods of people in poor developing countries.

Prior to this thesis, it was assumed that there would be a computational answer to the problem of geographic basis risk, but based on the results presented here that notion has been challenged if not completely dispelled. It is a noteworthy result that no statistical correlation could be found within small geographic areas and that best practice is to place a weather station at each insurable site. The problem of geographic basis risk is shown here to be a persistent and fundamental problem of weather index insurance.

Similarly, existing literature on the topic of weather index insurance has neglected to consider the presence of simultaneous risk events and their possible insurability. While the methods presented in this thesis are necessarily an outline that would need to be modified by insurers, the concepts are of undeniable value for risk management purposes. Deciphering weather criteria for the seemingly limitless number of crop pathogens, for instance, would be of immense value for both scientific and insurance purposes.

However, because of the amount of data available via Weather Wizard, this thesis relies heavily on computational methods that might not be available in places that have poor records, like developing countries. The methods presented in this document provide a theoretical background to fundamental problems (such as the confirmation of the influence of distance on rainfall correlation), but have more value in guidance than practical use. Although the methods presented in this paper represent a genuine step forward for the study of weather index insurance, there is still much work to be done.

Future Research

The development of the Weather Wizard website is likely a continuous process and will need to adapt and grow as the theoretical basis behind weather index insurance strengthens. It will be a challenge, to say the least, to maintain current technology and data without a major contribution from a future graduate student. However, Weather Wizard will likely be instrumental in processing the large amounts of data necessary for further research into pricing weather index insurance using the historical frequencies of the burn rate model, of which there are numerous possibilities, especially in the area of basis risk (both local and geographic.)

In addition, another look at the problem of geographic basis risk using more sophisticated spatial econometrics might prove fruitful. The findings of this paper point the way forward but it is possible the relationship between simple geographic variables and correlation might be improved using more sophisticated models than ordinary least squares (OLS) regression.

Chapter 7 - Technical Specifications

Software Vendors

Weather Wizard is written in ASP.NET using Microsoft Visual Studio 2005. The database platform used is Microsoft SQL Server 2003. On certain pages, data may be exported to Microsoft Excel format for graphing functions and more in-depth data manipulation. Third-party software includes NMath Core 2.2 and NMath Stats 2.1 by Centerspace Software for advanced regression statistics. Weather Wizard incorporates Zip Code data for weather station selection supplied by Datasheer L.L.C. through their website http://www.zip-codes.com.

On the state selection screen and again in the Basis Risk pages, the user may also click to display geographic data in Google Earth. This feature uses KML (Keyhole Markup Language), and requires Google Earth 4.1 to function correctly.

Data Summary

The data for this project is provided by the National Oceanic and Atmospheric Administration (NOAA), and includes weather data from nearly 25,000 weather stations over the years 1892 (at some stations) to 2001. Efforts are underway as of the date of this writing (May 22, 2008) to update the database to include data up until 2006.

Many similar studies or products only use a fraction of the data available because of concerns about the reliability of data more than 30 to 50 years old. For Weather Wizard, a conscious decision was made to include the most data possible, even if those data are incomplete. Metrics are in place to clean and replace data that is missing. Appendix 1 is a summary table of the data grouped at the state level. (Data is aggregated at the monthly level in this table not only because of the structure of the database but because it may be the most reliable indicator of content.) This table reveals for each state the amount of data available for each weather type as well as the total number of weather stations and the average months of data for each weather station.

Also of note in this table is that the most robust data set is precipitation data. Daily High and Low temperatures are on average about 70% as large, and Daily Mean temperatures 60%.

APPENDIX

Appendix A – Weather Wizard Screen Shots

Figure 9: Weather Wizard Main Screen

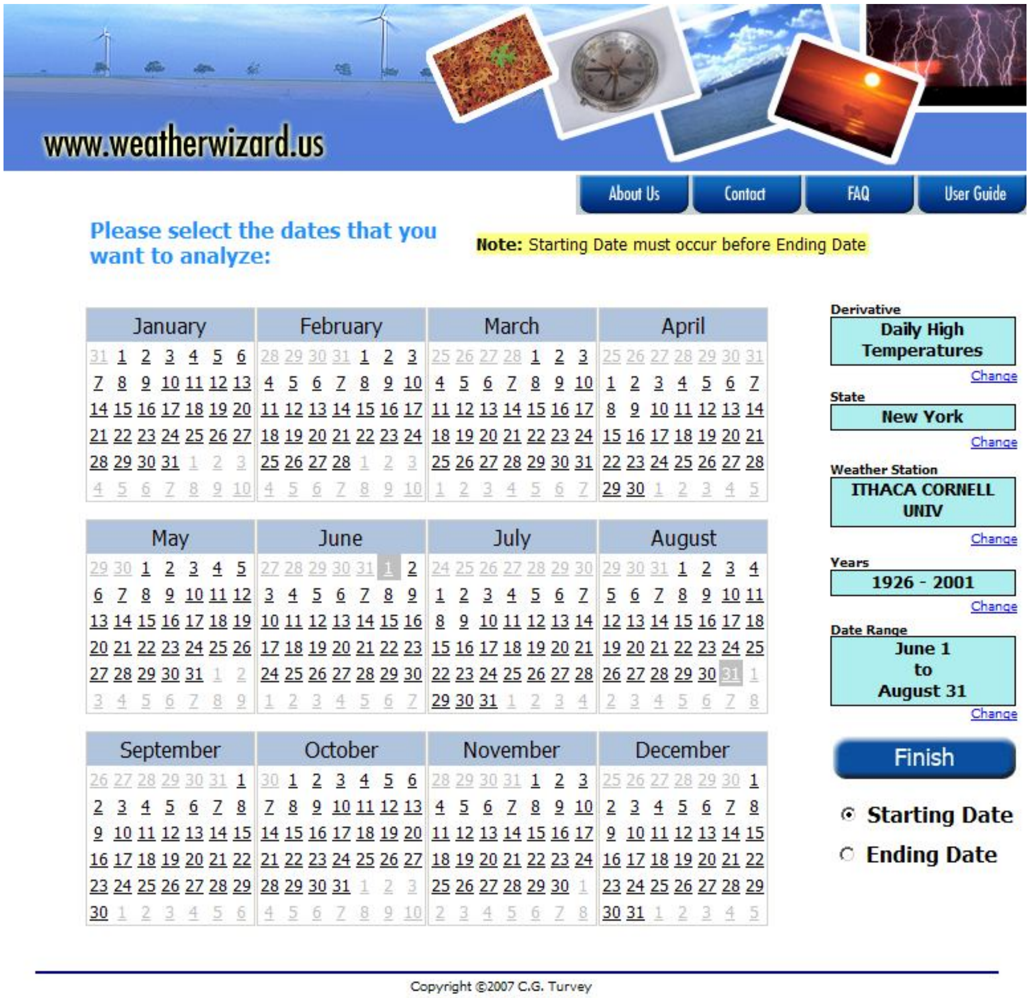

Figure 10: Date Selection Screen for Specific Event Risk

Item	DegreeDays	Payout	Avg Temp	Std. Deviation
Premium	$786.67			
Std. Dev Premium	$721.37			
Mean Degree Days	67.52			
Std Degree Days	57.47			
Max Degree Days	235.00			
Min Degree Days	2.00			
1926	62.00	$0.00	76.27	8.37
1927	46.00	$0.00	75.54	8.30
1928	49.00	$0.00	77.72	7.61
1929	49.00	$0.00	77.00	8.78
1930	121.00	$0.00	79.68	8.01
1931	166.00	$0.00	81.77	8.36
1932	77.00	$0.00	79.93	7.37
1933	220.00	$20,000.00	82.47	8.99
1934	153.00	$0.00	81.37	7.97
1935	103.00	$0.00	80.52	7.62
1936	204.00	$4,000.00	82.49	8.18
1937	173.00	$0.00	82.27	7.63
1938	180.00	$0.00	82.72	7.53
1939	155.00	$0.00	82.95	6.66

Figure 11: Temperature Insurance Worksheet

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Temperature Insurance Worksheet

For 91 Days; June 1-August 31

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Select Event Criteria

- ○ Less Than Or Equal To <=
- ◉ Greater Than Or Equal To >=

Select Payout Type for degree-day

- ◉ Lump Sum Payout
- ○ Unit Payout

Select Temperature Criteria

- ◉ Use Daily Temperatures
- ○ Use Cooling/Growing Degree Days
- ○ Use Heating Degree Days

Enter Degree Day Standard: 0

Enter Event Criteria: 85

Enter Event Length (Days): 5

Enter Number Of Events To Insure: 4

Enter Payout Per Event ($): 1000

Calculate Temperature Insurance

Multiple Event Summary

Item	# of Events	% or $Value	Avg Temp	Std. Deviation
Event Premium	$1,053.33			
Std. Dev. Premium	$1,089.18			
Minimum Premium	$0.00			
Maximum Premium	$4,000.00			
Chance of 0 events	25	0.3333		
Chance of 1 events	33	0.4400		
Chance of 2 events	10	0.1333		
Chance of 3 events	2	0.0267		
Chance of 4 events	5	0.0667		
1926	0	00.00	76.27	8.37
1927	1	1,000.00	75.54	8.3
1928	0	00.00	77.72	7.61
1929	1	1,000.00	77	8.78
1930	1	1,000.00	79.68	8.01
1931	1	1,000.00	81.77	8.36
1932	1	1,000.00	79.93	7.37
1933	4	4,000.00	82.47	8.99
1934	2	2,000.00	81.37	7.97
1935	1	1,000.00	80.52	7.62
1936	2	2,000.00	82.49	8.18

1 2 3 4 5

Multiple Event Probability Matrix

Event	1	2	3	4
1	1.0000	0.3400	0.1400	0.1000
2		1.0000	0.4118	0.2941
3			1.0000	0.7143
4				1.0000

Figure 12: Temperature Insurance Worksheet illustrating excess heat risk


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Precipitation Insurance Worksheet
For 91 Days; June 1-August 31

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Select the Event Criteria
- (•) Less Than Or Equal To <=
- ( ) Greater Than Or Equal To >=

Select Payment Type
- (•) Lump Sum Payout
- ( ) Unit Payout

Select Rainfall Measure to Use
- ( ) Use Daily Precipitation
- (•) Use Cumulative Daily Precipitation

Enter Precipitation Event Criteria (e.g Inches): 1
Enter Specific Event Lengths (Days): 21
Enter Number of Events to Insure: 3
Enter Payout per Event ($): 1000

Calculate Precipitation Insurance

Precipitation Insurance Summary

Item	# of Events	% or $Value	Avg. Rainfall	Cumulative Rain
Average Daily Rain	0.12			
Std Daily Rain	0.03			
Average Cumulative Rain	10.74			
Std Cumulative Rain	2.77			
Event Premium	$1,000.00			
Std. Dev. Premium	$993.13			
Minimum Premium	$0.00			
Maximum Premium	$3,000.00			
Chance of 0 events	29	0.3919		
Chance of 1 events	23	0.3108		
Chance of 2 events	15	0.2027		
Chance of 3 events	7	0.0946		
1926	1	1,000.00	0.11	9.76
1927	3	3,000.00	0.07	6.65
1928	0	00.00	0.13	11.74
1929	1	1,000.00	0.14	12.42
1930	1	1,000.00	0.13	12.09
1931	2	2,000.00	0.06	5.78
1932	0	00.00	0.10	9.41
1933	0	00.00	0.14	13.04

1 2 3 4 5

Multiple Event Probability Matrix

Event	1	2	3
1	1.0000	0.4889	0.1556
2		1.0000	0.3182
3			1.0000

Figure 13: Precipitation Insurance Worksheet

Appendix B – Site Map for Weather Wizard

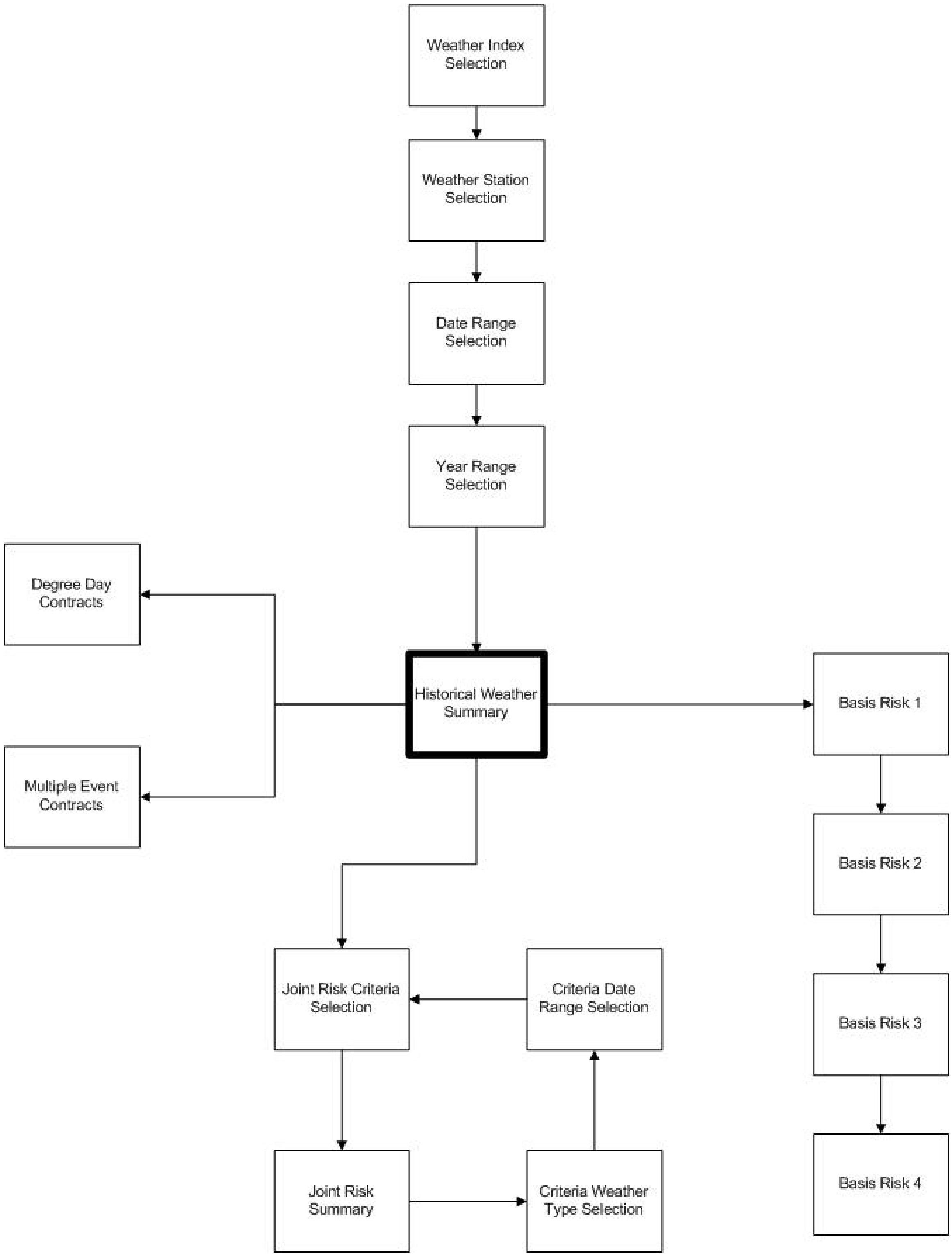

Figure 14: Flow Chart for Weather Wizard

Appendix C – State by State Data Summary

State	Daily High	Daily Mean	Daily Low	Rainfall	Total Obs.	# Stations	Avg./Station
Texas	277,051	225,519	276,792	500,717	**1,280,079**	1671	766.06
Montana	169,727	146,977	169,584	204,062	**690,350**	716	964.18
California	140,584	113,741	140,464	229,878	**624,667**	1760	354.92
Arizona	138,690	121,209	138,519	178,467	**576,885**	569	1,013.86
Oregon	125,166	108,350	125,076	150,545	**509,137**	775	656.95
Kansas	98,506	76,660	98,508	191,682	**465,356**	778	598.14
New Mexico	111,857	96,661	111,779	142,713	**463,010**	617	750.42
Colorado	112,026	90,019	112,027	144,542	**458,614**	631	726.81
Washington	111,442	96,309	111,415	129,734	**448,900**	635	706.93
Nebraska	95,989	83,832	95,984	161,588	**437,393**	576	759.36
Utah	106,211	94,935	106,177	119,714	**427,037**	582	733.74
Missouri	96,476	88,826	96,555	143,072	**424,929**	512	829.94
Iowa	101,055	90,052	101,035	127,594	**419,736**	505	831.16
Illinois	101,055	90,052	101,035	127,594	**419,736**	550	763.16
Oklahoma	93,145	84,726	93,037	145,056	**415,964**	472	881.28
Pennsylvania	86,062	72,918	85,983	155,876	**400,839**	678	591.21
Wisconsin	94,756	88,907	94,715	120,419	**398,797**	343	1,162.67
North Carolina	88,109	76,757	88,071	131,387	**384,324**	480	800.68
Minnesota	90,629	78,878	90,753	118,539	**378,799**	388	976.29
New York	79,697	66,695	79,701	146,728	**372,821**	688	541.89
Idaho	93,713	82,464	93,660	95,953	**365,790**	482	758.90
South Dakota	87,517	77,214	87,420	112,787	**364,938**	370	986.32
Wyoming	90,005	71,801	89,932	104,242	**355,980**	513	693.92
Ohio	83,549	61,533	83,474	126,596	**355,152**	478	743.00
Michigan	85,134	70,452	85,077	104,863	**345,526**	575	600.91
North Dakota	81,607	72,005	81,567	106,126	**341,305**	347	983.59
Alaska	89,023	63,853	88,993	88,843	**330,712**	677	488.50
Arkansas	69,082	61,748	69,008	114,186	**314,024**	419	749.46
Georgia	71,383	58,147	71,244	111,718	**312,492**	376	831.10
Indiana	71,350	65,993	71,338	95,776	**304,457**	459	663.31

Florida	75,827	75,741	61,165	85,101	**297,834**	353	843.72
Tennessee	61,616	53,218	61,581	108,108	**284,523**	503	565.65
Virginia	63,179	55,368	63,080	101,592	**283,219**	424	667.97
Alabama	58,399	51,614	58,378	107,931	**276,322**	363	761.22
Mississippi	56,593	52,181	56,547	99,791	**265,112**	355	746.79
Louisiana	55,719	48,084	55,716	100,905	**260,424**	491	530.40
Kentucky	48,818	43,489	48,737	103,875	**244,919**	490	499.83
West Virginia	56,626	49,258	56,631	81,133	**243,648**	392	621.55
Nevada	62,845	49,379	62,745	64,295	**239,264**	365	655.52
Hawaii	32,058	14,518	31,988	153,142	**231,706**	675	343.27
South Carolina	48,201	42,563	48,164	66,623	**205,551**	219	938.59
Maryland	41,241	35,943	41,211	45,420	**163,815**	227	721.65
Massachusetts	30,698	24,983	30,705	53,791	**140,177**	208	673.93
New Jersey	31,199	26,459	31,202	46,505	**135,365**	176	769.12
Maine	33,113	25,762	33,108	41,109	**133,092**	202	658.87
New Hampshire	21,668	18,105	21,659	36,851	**98,283**	183	537.07
Vermont	17,610	15,340	17,597	30,647	**81,194**	152	534.17
Connecticut	16,526	12,802	16,525	32,717	**78,570**	142	553.31
Delaware	5,695	4,710	5,694	5,825	**21,924**	26	843.23
Rhode Island	3,435	1,759	3,439	4,178	**12,811**	20	640.55

Appendix D – Code Samples

Sample 1: Dat a Cleaning Algorithm

```
  While myReader.Read() And bSameStation
      itblWeatherStationCode = myReader.Item("WeatherStnCode")
      itblYear = myReader.Item("Year")
      itblMonth = myReader.Item("Month")
      PrcrSnowChanges = 0
      If bstart And sqlstart <> itblYear Then LastYear = itblYear
      End If
      bstart = False
      'SKIP if year omitted
      For i = 0 To yearOmit.Count - 1
          If itblYear = yearOmit.Item(i) Then GoTo skip
      Next

      'Change all 99999s to 0s on rainfall
      For i = 1 To DaysInMonth(itblMonth, 2006)
          Dim strDayCol As String = "Day" & Format(i)
          inin(gh, 0) = i & "/" & myReader.Item("Month") & "/" & myReader.Item("Year")
                    inin(gh, 1) = myReader.Item(strDayCol).ToString
                    gh += 1
                    If gh > (old_Year + 1) * (DayCount + 1) Then gh = (old_Year + 1) *
(DayCount + 1)
                    If myReader.Item(strDayCol).ToString = "99999" And (nature = 4)
Then
           itblDay(i - 1) = 0
           PrcrSnowChanges = PrcrSnowChanges + 1
       Else
           itblDay(i - 1) = myReader.Item(strDayCol)
       End If
       If nature = 4 Then
           itblDay(i - 1) = itblDay(i - 1) / 100
       End If
   Next

   'Get starting and ending days
   xMonth = itblMonth
   xYear = itblYear
   xDays = DaysInMonth(xMonth, 2006)
   If Not switched Then
       If xMonth = monstart Then
           iStartDate = daystart
       Else
           iStartDate = 1
       End If
       If xMonth = monend Then
           iEndDate = dayend
       Else
           iEndDate = xDays
       End If
   Else
       If xMonth = monend Then
           iStartDate = dayend
       Else
           iStartDate = 1
       End If
       If xMonth = monstart Then
           iEndDate = daystart
       Else
           iEndDate = xDays
       End If
   End If

y:
                For j = iStartDate To iEndDate
```

```
GetNumbers = 1
GetLastValue = 0
avgValue = 0.0

If itblDay(j - 1) = "99999" Then
    If j = iStartDate Then
        iStartDate = iStartDate + 1

        GoTo y ' Start over with one less day... Kind of a cheater...
    ElseIf j = iEndDate Then
     itblDay(j - 1) = itblDay(j - 2) ' Last data point, again: kind of a cheater
   Else
       For ik = (j - 1) To iEndDate - 1

           If itblDay(ik) <> 99999 Then
               GetLastValue = ik
               GoTo exitInnerLoop
           Else
               GetNumbers = GetNumbers + 1
           End If
       Next
exitInnerLoop:
              If itblDay(GetLastValue) > itblDay(j - 2) Then
                  avgValue = (itblDay(GetLastValue) - itblDay(j - 2)) / GetNumbers
              ElseIf itblDay(GetLastValue) < itblDay(j - 2) Then
                  avgValue = (itblDay(j - 2) - itblDay(GetLastValue)) / GetNumbers
            ElseIf itblDay(GetLastValue) = itblDay(j - 2) Then
                avgValue = 0
            End If

            If itblDay(GetLastValue) > itblDay(j - 2) Then
                For ik = (j - 1) To (GetLastValue - 1)
                    itblDay(ik) = itblDay(ik - 1) + avgValue
                Next
            ElseIf itblDay(GetLastValue) < itblDay(j - 2) Then
                For ik = (j - 1) To (GetLastValue - 1)
                    itblDay(ik) = itblDay(ik - 1) - avgValue
                Next
            ElseIf itblDay(GetLastValue) = itblDay(j - 2) Then
                For ik = (j - 1) To (GetLastValue - 1)
                    itblDay(ik) = itblDay(ik - 1)
                Next
            End If ' setting averages
        End If ' j not start or end date
    End If ' not a 999999

    k = k + 1
    If LastYear = xYear And DayInYear <= DayCount + 1 Then
        If k = 1 Then
            DayInYear = 1
            YearCount = 0
        Else
            DayInYear = DayInYear + 1
        End If
    Else
        DayInYear = 1
        YearCount = YearCount + 1
    End If
    a_Setup(k - 1, 0) = k
    a_Setup(k - 1, 1) = xYear
    a_Setup(k - 1, 2) = xMonth
    a_Setup(k - 1, 3) = j
    a_Setup(k - 1, 4) = DayInYear
    a_Setup(k - 1, 5) = itblDay(j - 1)
    a_CrossRef(YearCount, DayInYear - 1) = itblDay(j - 1)
    a_Year(YearCount) = xYear
    LastYear = xYear
Next
skip:           i = i + 1
```

Sample 2: Degree Day payout algorithm

```
For j = 0 To DayCount - 1
   If dd_type = 2 Then   ''for heating degree days
      yevent = IIf(target - yearvalues(j) > 0, target - yearvalues(j), 0)
          cdd = cdd + yevent
      End If
      If dd_type = 1 Then ''for cooling or growing degree days
        yevent = IIf(yearvalues(j) - target > 0, yearvalues(j) - target, 0)
        cdd = cdd + yevent
    End If
Next
cdd = Format(cdd, "##,##0.00")  'this is CDD for each year

If LorG = 0 Then
    If cdd <= criteria Then
        If Session.Item("br_payouttype") = 0 Then Return 1000
        Return (criteria - cdd) * Payout
    Else
        Return 0
    End If
End If
If LorG = 1 Then
    If cdd >= criteria Then
        If Session.Item("br_payouttype") = 0 Then Return 1000
        Return (cdd - criteria) * Payout
    Else
        Return 0
    End If
End If
```

Sample 3: Multiple Event Contract algorithm

```
For j = 0 To daycount - 1
    If LorG = 0 Then
        If yearvalues(j) <= criteria Then
            icount = icount + 1
            If icount = eventlength Then
                eventcount = eventcount + 1
                icount = 0
            End If
        Else
            icount = 0
        End If
    End If
    If LorG = 1 Then
        If yearvalues(j) >= criteria Then
            icount = icount + 1
            If icount = eventlength Then
                eventcount = eventcount + 1
                icount = 0
            End If
        Else
            icount = 0
        End If
    End If
Next
If eventcount > Session.Item("br_NumEvents") Then eventcount =
Session.Item("br_NumEvents")
Return eventcount * Payout
```

Sample 4 : Cumulative Rainfall Payout algorithm

```
For j = 0 To DayCount + 1
    '****************************************************************
    If j > overlap - 1 Then
        cumrain = 0
        For k = 1 To eventlength   'sum up previous days
             cumrain = cumrain + yearvalues(j - k) 'xMatrix(i, j + 1 - k)
        Next k
        If LorG = 0 Then
            If cumrain <= criteria Then
                eventcount = eventcount + 1
                unitpayout = unitpayout + (criteria - cumrain) * 1000    'cgt 21/05/07
                cumrain = 0
                overlap = j + eventlength
            End If
        Else
        If cumrain >= criteria Then
             eventcount = eventcount + 1
             unitpayout = unitpayout + (cumrain - criteria) * 1000
             cumrain = 0
             overlap = j + eventlength
        End If
     End If
End If

Next
'************************************************************************
If Session.Item("br_payouttype") = 0 Then
    If eventcount > Session.Item("br_NumEvents") Then eventcount =
Session.Item("br_NumEvents")
    results = eventcount * Payout
Else
    If eventcount > Session.Item("br_NumEvents") Then
        results = unitpayout * Session.Item("br_NumEvents") / eventcount
    Else : results = unitpayout
    End If
End If
```

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