Review of Business and Economics Studies
2018, Vol. 6, No. 1, 29–42

DOI: 10.26794/2308-944X-2018-6-1-29-42

Weather Derivatives in Russia: Farmers' Insurance against Temperature Fluctuations

Eric Carkin[2], Stanislav Chekirov[3], Anastasia Echimova[3], Caroline Johnston[1,2], Congshan Li[2], Vladislav Secrieru[3], Alyona Strelnikova[3], Marshall Trier[2], Vladislav Trubnikov[3]

[1]main draft editor, derivative pricing research
[2]Worcester Polytechnic Institute, MA, USA
[3]Financial University under the Government of the Russian Federation, Moscow, Russia

Abstract

This project proposes the use of weather derivatives, a type of financial instrument with a payout based on weather conditions, as a method for Russian farmers to hedge against daily temperature fluctuations. We created a weather derivative simulation tool in Microsoft Excel that calculates the effect of temperature on crop yield and then analyzes how the return of weather derivatives can potentially compensate for crop loss. Based on this tool, we developed a series of recommendations to help implement this system of protection with real users.

Keywords: weather derivatives; temperature fluctuations; hedge; crop loss
JEL classification: G13, G17, Q18

Utilizing Weather Derivatives in Russia

In 1998 it was estimated that 20% of the world economy is vulnerable to weather conditions (Barrieu & Scaillet, 2010). Weather is one of the most uncontrollable and influential variables within the agriculture sector, becoming increasingly unpredictable as climate change continues to affect global weather patterns. In some cases, extreme weather can cause up to a 40% deficit in crop yields in Russia, potentially devastating a farmer's economic income (Pavlova, Varcheva, Bokusheva, & Calanca, 2014). However, by utilizing various types of insurance, those in the agricultural sector can mitigate their exposure to this financial risk.

Russia's ambitions to become agriculturally self-sufficient and its ban on imported crops have caused its agricultural sector to grow substantially in recent years (Liefert, Serova, & Liefert, 2015). To foster this growth and develop this sector, farmers need insurance policies to protect themselves from risks that are beyond their control, such as weather. Weather derivatives, a type of financial option, can be used to protect farmers from daily fluctuations in temperature and precipitation that catastrophic insurance plans do not shield them from (Chung, 2011). These events have a modest effect over a single day but cumulatively they can have severe effects on a farmer's yield by the end of the growing season. Though weather derivatives have been used to hedge against risks in other countries, Russia has yet to explore this tool and popularize it among its farmers (Esper Group, 2010).

The goal of this project is to create a proof-of-concept weather derivatives pricing system. This system will explore the feasibility of farmers' insurance within Russia using such financial instruments. Farmers will be able to hedge against weather-related risks by trading weather derivative options and to remain financially stable in times of fluctuating weather conditions. To accomplish this goal, we had to meet the following objectives:

Determine the relationship between temperature and crop yields within the Moscow, Krasnodar, and Omsk regions (see Figure 1)

Price weather derivative options

Create an Excel tool to simulate the financial impact of weather derivatives for users

Using Weather Derivatives to Insure Russian Agriculture

To implement a weather derivatives system within Russia, one must understand the rela-

Figure 1. Regions of focus: Left-Krasnodar, Center-Moscow, Right-Omsk.

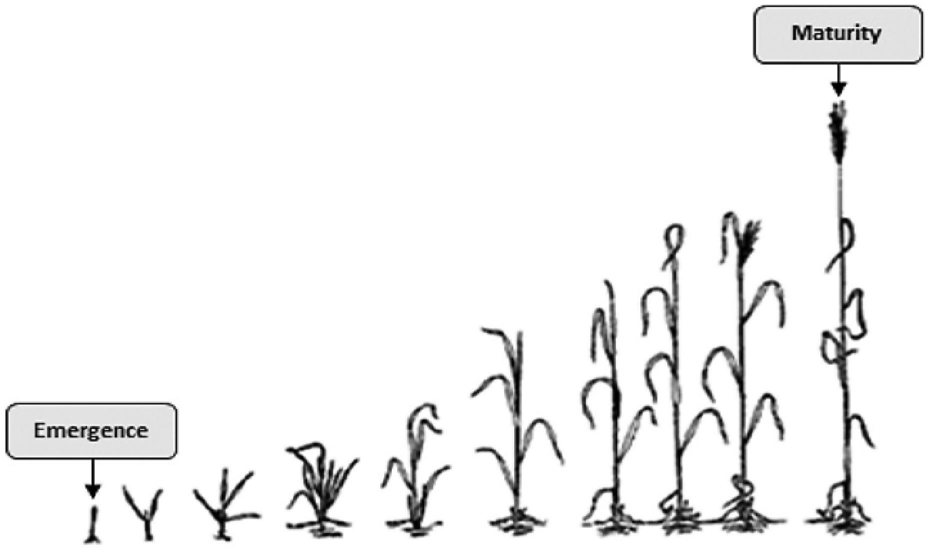
tionship between weather and agriculture and the current measures in place to protect farmers against weather risks. In this chapter, we will explain the concept of a weather derivative to hedge against these risks. Then we will discuss Russia's current agricultural economy and strategies to protect those working in agriculture from losses due to weather events.

Weather risks and mitigation strategies. The associated economic risks tied to weather can be divided into two major groups: high frequency-low risk events and low frequency-high risk events. Low frequency-high risk events, such as tornadoes and hurricanes, have an extreme, immediate impact, costing millions of dollars in damages. High frequency-low risk events are everyday weather phenomena, such as rain and temperature change. These events cause little impact over a single day but cumulatively can cause substantial negative effects. The agricultural sector is especially sensitive to this type of risk, causing weather to have a considerable effect on the economy (Barrieu & Scaillet, 2010).

Governments across the globe have set up various forms of insurance, such as government subsidies or weather derivatives, to protect those in the agricultural sector. The use of subsidies in times of poor harvest, however, is not always ideal or even feasible for less developed countries that cannot generate enough revenue from taxation. Additionally, subsidy compensation is based on a farmer's exact loss, requiring insurers to determine farmer's yields to calculate what compensation is due. This increases costs to the insurer and raises the cost of premiums for those who are insured (Chung, 2011).

Weather derivatives. Weather derivatives offer advantages to both small-scale farmers and corporate agricultural businesses. These derivatives are a type of option with an index-based payout, modeled after predicted future weather conditions over a certain period. The major difference between a weather derivative and subsidy is that the payout for a derivative is based on the specific weather conditions that cause farming loss, while a payout for a subsidy is based on the actual loss itself. Thus, weather derivatives can cover the high frequency-low risk events described above without the need for insurers to determine farmer's exact yields, keeping premium costs lower. However, a substantial amount of meteorological data is required to price the derivative (Chung, 2011).

Around 75% of all weather derivative transactions are based upon temperature predictions while 10% of transactions are based on rainfall (Barrieu & Scaillet, 2010). Temperature-indexed weather derivatives revolve around the concept of Growing Degree Day (GDD), which measures



Days after emergence	12	15	23	28	34	38	41	45	85
Cumulative GDD	170	230	430	500	690	810	895	990	2260

Figure 2. Adapted from 'Growth and Development Guide for Spring Wheat' (Simmons, Oelke and Anderson, 1985).

heat accumulation to predict favorable plant development rates and stages of growth (see Figure 2, Appendix A). The metric below computes the difference between realized temperatures to a baseline temperature, which varies depending on the crop species.

Non-Russian weather derivatives systems. While weather derivatives are still a fledgling concept, being first traded on the Chicago Mercantile Exchange (CME) in 1999, their use is slowly becoming more commonplace within global markets (Barrieu & Scaillet, 2010). The Canadian agricultural insurance market recently introduced weather derivatives to insure against abnormal season temperatures or precipitation levels. After interviewing 397 farmers from Saskatchewan over a period of three years, investigators showed that 307 of these farmers used only traditional agricultural insurance, 37 only used weather derivatives, and 37 used both types of insurance. The study concluded that this wide disparity in weather derivative use is mainly attributed to farmers' lack of "awareness and understanding" of the tool (Van Camp, 2015, para. 5). About half of the participants who did not invest in weather derivatives were not aware that such a tool was available to them. About one-third of these farmers felt they did not have enough knowledge and skill to utilize the derivative (Van Camp, 2015).

In 2003, a Mumbai insurance company implemented weather derivatives for small groundnut and castor farmers in four villages within the Andhra-Pradesh state. The program encouraged farmers to attend educational workshops about the product to inform farmers of this insurance and its benefits, increasing the derivative's approachability. In 2005 after more improvements to the program, "more than 250,000 [sic!] farmers bought weather insurance" (Barrieu & Scaillet, 2010, 7). This pilot project was deemed a major success and inspired many more weather-based insurance schemes across India such as the Weather-based Crop Insurance Scheme (WBCIS) (Ministry of Finance of India, 2017).

One of the main distinctions between the Indian and the Canadian weather derivatives program is the presence of an educational program for the users. Equipped with the knowledge of how these weather derivatives could financially support them, farmers in India widely supported the weather derivatives system. However, those in Canada struggled to see the potential benefits of these tools or were completely unaware of them. Thus, to build a successful and accessible weather derivative system, it is vital to educate the users.

Agriculture in the Moscow, Krasnodar, and Omsk regions. The Russian agriculture sector employs 7.7 million people, or 12% of the total

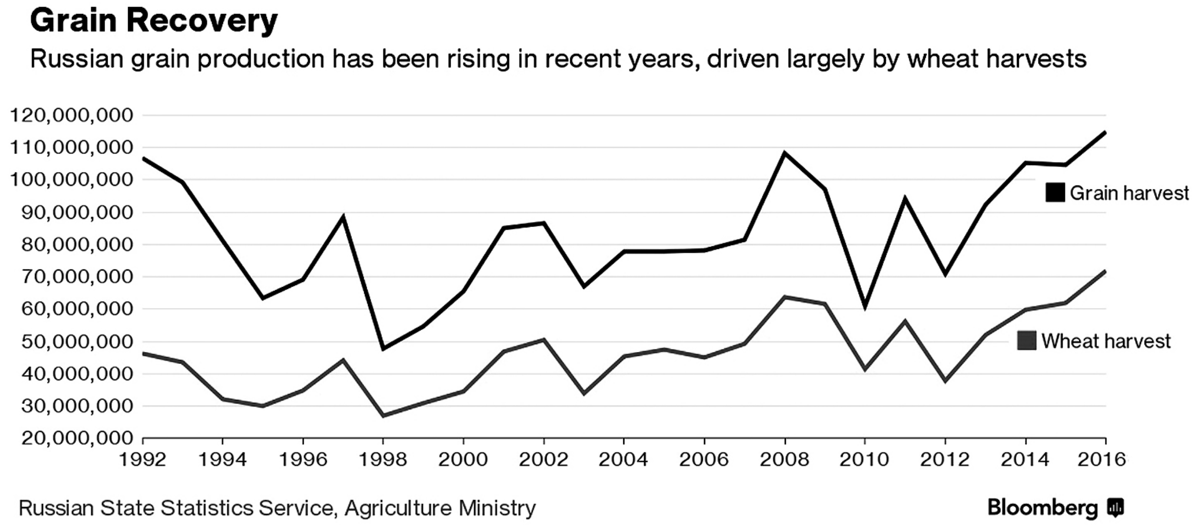


Figure 3. Russian grain production 1992–2016 (Medetsky, 2016).

workforce (British Potato Council, 2006). Most of Russia's land mass is in "risky farming zones," where harvest capacity depends largely on weather conditions. This is exacerbated by global climate change, making weather conditions increasingly unpredictable. Because of the country's geographic span, the overall climate of Russia varies significantly from area to area, allowing different crops to thrive in different temperatures (Country Studies, 1996). These differences not only affect the rate of crop growth, but also the crops' planting and harvest dates, creating a unique set of growing conditions in each region.

Wheat, corn, and potatoes are three of the most widely-grown crops within Russia (Basic Element, 2013). Grains occupy more than 50% of the available cropland, primarily in the form of wheat (Country Studies, 1996). Overall land productivity has recently increased due to a decrease in the price of the ruble and recent favorable growing conditions (see Figure 3) (Medetsky, 2016). These large yields have brought in a substantial income for farmers, but only because of favorable weather conditions. Thus, the agricultural sector is currently a lucrative investment area.

The Moscow, Krasnodar, and Omsk regions provide a representative range of Russian climatic and agricultural conditions. The Moscow region is in the western part of the country. Because of its large population, its local agriculture has a high profile. Krasnodar is the economic center of southern Russia, and 42.8% of its main industries is agriculture-based (Oleynik, 2013). Because of Krasnodar's geolocation by the Black Sea, the region has a longer growing season and ideal weather conditions for plant growth (State's executives of the Krasnodar Region, n.d.). Conversely, the growing conditions in Omsk are not as favorable. Situated on the West Siberian Plain, the annual average temperature in Omsk is around 1.4°C (Climatemp, n.d.). Wheat, corn, and potatoes are grown in all three areas, but each is subject to the region's unique weather conditions.

The shortcomings of the Russian Government subsidies system. Government subsidies are currently used to help farmers in Russia hedge against weather risks (Buckley, 2017). State-issued subsidies have created significant growth within the agricultural sector, but not without complications. Some farmers cannot afford premiums, meet land acreage requirements, or obtain the necessary accounting paperwork to qualify for payments. In the 2012 drought, state compensation was only given to farmers "located in emergency districts… in a manner that was not at all transparent [to the farmers]," while those located in "non-emergency" zones suffered terrible losses as well (Ukhova, 2013, 12). Those who received payment received insufficient amounts in comparison to their actual loss. This underperformance by subsidies has resulted in a general lack of faith in the system (Ukhova, 2013). To work to remedy this, farmers must be able to easily access their method of compensation and understand why they are receiving it. Even with these improvements, subsidies only protect against high-impact events such as droughts. There is still a clear lack of protection against small but continual risk such as temperature fluctuations (Esper Group, 2010).

Conclusions. Weather derivatives can be used to insure farmers against daily fluctuations in temperature, which can have a substantial impact on their yields and wallets. Most of the farmland within Russia is highly sensitive to weather conditions. Though government subsidies have been used in the past to assist farmers in protecting themselves against weather risks, farmers no longer trust this system. Weather derivatives, however, use objective weather data to help farmers compensate for their losses incurred by unfavorable weather conditions. As shown in the Indian and Canadian cases, for the concept of weather derivative to work it must be familiar to farmers, and it is vital that they are educated about this tool's use and benefits. This builds trust and extends the use of an effective weather derivatives system.

Methodology: Developing a Weather Derivatives System

The goal of this project is to create a proof-of-concept weather derivatives pricing system. This system will explore the feasibility of farmers' insurance within Russia using such financial instruments. We created the following objectives to successfully reach this goal:

1. Determine the relationship between temperature and crop yield within the Moscow, Krasnodar, and Omsk regions
2. Price weather derivative options
3. Create an Excel tool to simulate the financial impact of weather derivatives for users.

Determining relationship between temperature and crop yield. Because the pricing of weather derivatives depends upon GDDs that are crop-specific, we selected 3 regions and 3 specific crop types for the construction of derivatives. We identified corn, potatoes, and wheat (spring and winter) as some of the most common crops in Russia and the Moscow, Krasnodar, and Omsk regions as areas representing a spread of weather conditions. We gathered each crop's baseline temperature for its GDD calculation, its planting dates, and its harvest dates. Using these dates and temperatures, we accurately gauged the temperatures these crops experience within a growing season. We calculated the mean cumulative GDD experienced by each crop within the Moscow, Krasnodar, and Omsk regions from the years 1996 to 2015 with data from the meteo.ru (RIHMI-WDC) weather database and collected regional crop yield statistics from Knoema, another online database (see References). Using Microsoft Excel, we developed a database of these temperatures and implemented an ordinary least squares regression technique to quantify the relationship between cumulative GDD over the growing period and crop yield.

Pricing weather derivatives. To price the derivatives, we surveyed various pricing methods. After reviewing literature by Sun and van Kooten (2015); Groll, López-Cabrera, & Meyer-Brandis (2016); Taylor & Buizza (2006); Chung (2011); Alaton, Djehiche, & Stillberger (2002); Barrieu & Scaillet (2010); and Consedine (2000), we chose the historical burn analysis method, which takes the average historical GDD as the expected GDD for future years (see Appendix A). This technique was chosen because of its ability to accurately model these future GDD values, the accessibility of the data needed for this method, and the ability to conduct the necessary mathematical processes in a familiar format such as an Excel spreadsheet.

Creating simulation tool. To visually represent the results of this project and demonstrate the potential impact of this weather derivatives system, we created a weather derivative simulation tool in Visual Basic for Excel. This tool calculates the potential losses a farmer faces by interfacing with the GDD/yield relationship model. The farmer inputs his/her farm size, crop type, and location. His/her projected yield for the upcoming year is then calculated by utilizing the appropriate GDD/yield model, the projected GDD based on his/her region, and the size of his/her farm. This yield is then multiplied by the estimated worth of his/her crop, data gathered from Bloomberg, converting his/her potential profit to a monetary value.

Based on the GDD/yield model, the tool also estimates potential economic loss if the weather varies from the expected GDD. A derivative is then constructed using the chosen tick size. The derivative's payoff can be compared to a farmer's potential loss, showing its potential effectiveness as a form of insurance. The tool draws upon values from the database mentioned in Section 3.1. Because all the data inputs (excluding those provided by the user) are contained within Excel spreadsheets, the tool can be easily updated to include more recent information or different areas and crops, expanding it to become a more encompassing and accurate tool.

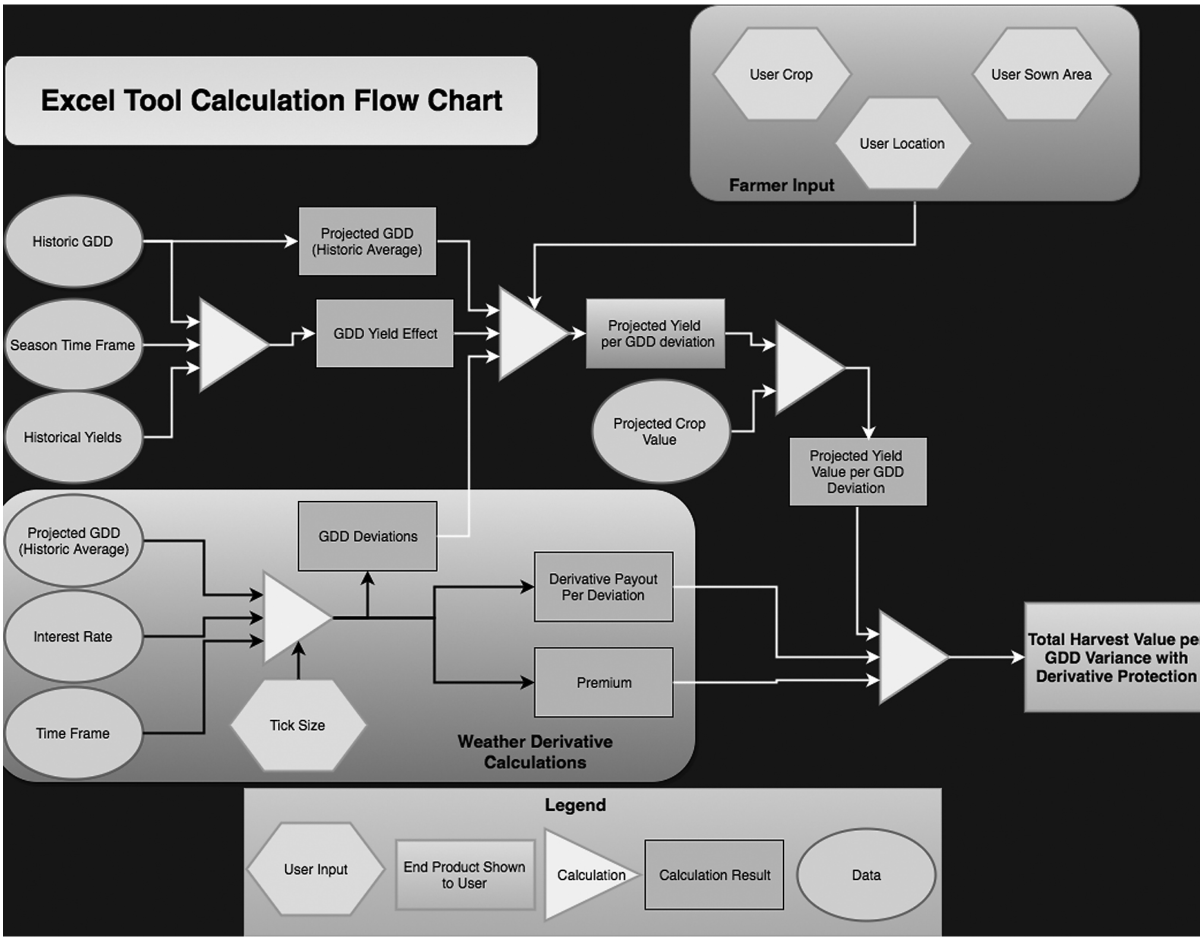


Figure 4. The main components of weather derivative simulation tool.

Conclusions. The cumulative application of our methods is showcased in the simulation tool. The tool can evaluate the GDD/yield relationship for each region and crop, the predicted GDD values for future years, and the potential profit or loss with weather derivative use for a specific user. This allows the user to visualize the effect of a weather derivative and its potential as an insurance measure. Additionally, the tool is easily modifiable, allowing it to remain relevant and open for modification while further developments take place in this research field. By using this tool, those who are interested in developing derivative-based insurance can also test their own research methods and display these techniques to their target users.

Results and Discussion

After initial poor results in our regression analysis for cumulative GDD and crop yield, we found there were large flaws in the methods in which we were processing and interpreting our collected data. We then developed a strategy to correct these flaws to pre-process our data to eliminate trends that were contaminating our results. This leads to more accurate results, producing a clearer relationship between the two variables. When pricing the derivative, the historical burn analysis generated high-quality GDD predictions and generally low premiums for the farmers. Both the regression and the pricing calculations were implemented in our Excel simulation tool that is both flexible for those who wish to build upon it and approachable for farmers who wish to use it.

Determining Relationship between Temperature and Crop Yield

The regression between temperature and crop yield initially yielded weak results and no clear or logical relationship has been obtained at that point (see Figure 5). After discussing the quality of our data, we isolated the causes of this weak regression result to two factors:

1. Qualitative growing season data
2. Skewed yield data

When collecting harvest and planting dates, we found that the data was extremely qualitative, described as "early May", "mid-September", etc. This is reasonable for a farmer who plants when the soil

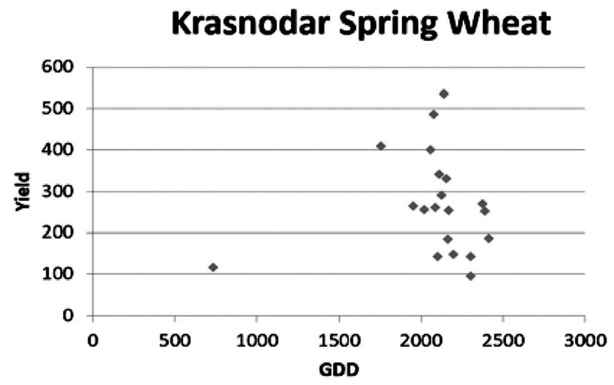


Figure 5. Krasnodar spring wheat GDD/yield before data pre-processing (1996–2015)

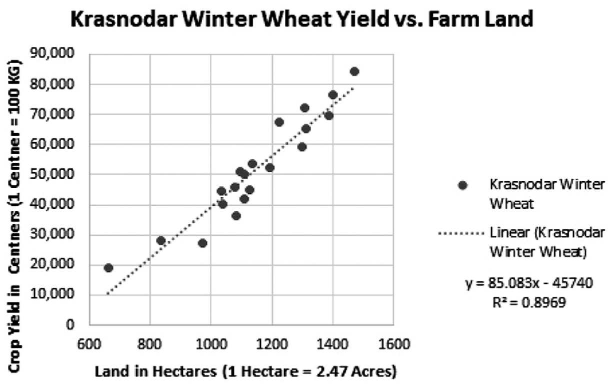


Figure 6. The trend between acreage and crop yield for Krasnodar winter wheat (1996–2015).

Table 1

Yield Per Area vs Cumulative GDD Regression R 2 Values

Crop	Moscow	Krasnodar	Omsk
Corn	0.276	0.201	0.137
Potato	0.026	0.247	0.195
Spring Wheat	0.211	0.428	0.26
Winter Wheat	0.083	0.259	0.057

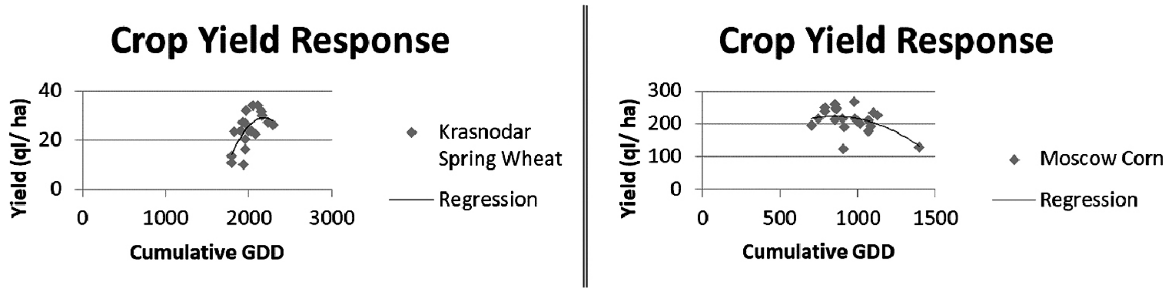


Figure 7. Krasnodar spring wheat and Moscow corn regression results (1996–2015).

is deemed ready, but not sufficient for quantitative analysis. To accurately model these decisions, we further researched the favorable planting conditions for our four crops. Then, based on this information, we created an algorithm to search through the temperature database and select a planting day that meets these conditions.

Each crop has its respective GDD criteria to meet to reach its planting date. However, GDD is not the only factor used. The typical growing season for our chosen crops covers a period of three months. Thus, our algorithm selects a planting date that satisfies the GDD requirements within this time range. If this criterion was not met during this period, the end of the time interval was selected as the planting date. This method of selecting planting dates creates a more accurate picture of actual GDD, giving us stronger models to predict crop growth. Harvest dates, on the other hand, remain relatively stable from year to year and do not require such attention.

We then realized that our collected yield data had varying amounts of total acreage per year contributing to this yield. An increased total acreage was resulting in an increased total yield for that year, i.e. causing a linear trend within the data (see Figure 6). Thus, to isolate the effects of GDDs on crop yield, we converted the raw yield data into yield per recorded acreage. The regression analysis then produced varying results (see Figure 7 and Table 1). Thus, this relationship can be used to approximate how a predicted change in cumulative GDD in each region will affect the yield results for each crop, demonstrating the farmers' potential loss in yield. This is the first step in showcasing

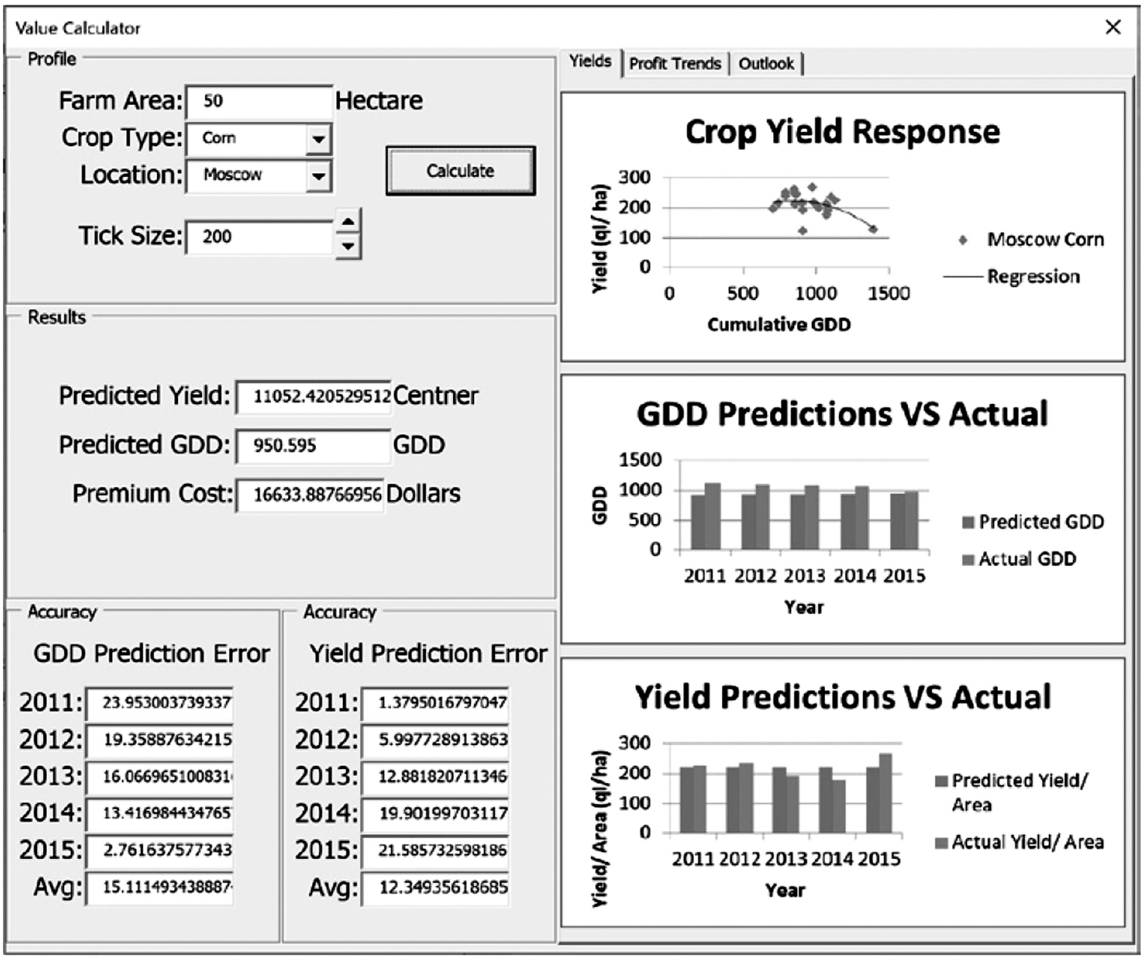


Figure 8. Weather derivative simulation tool interface.

to them how the purchase of weather derivatives can compensate for this projected loss.

Pricing Weather Derivatives

Following the formulas for pricing the weather derivatives, the farmer profits whenever the GDD hits one of two appropriate points (see Appendix A). However, it was not clear how to adjust these pricing parameters so that farmers with a larger amount of farmland and a greater economic loss from poor weather conditions would be able to buy a weather derivative to collect a larger payout. In other words, we could not establish a relationship between farm size and premium. Therefore, we added tick size as a user input for our simulation tool.

Creating Simulation Tool

The final deliverable of our project is an easy-to-use tool that compiles all our work and demonstrates the effectiveness of weather derivatives to farmers, while also serving as a stepping stone for a practical implementation of this project. The tool performs situation-specific calculations based upon profile information provided by the user, e.g. crop type, location, farm size, and tick size (see Figure 8). Using this information as a basis for our parameters, the tool draws from an Excel database to calculate the GDD/yield relationships, predicted GDDs and yields, the potential profit/loss of the farmer, and the price of the weather derivative. The farmer is then able to see his/her potential loss under various circumstances.

The program offers a large amount of flexibility in terms of upkeep, update potential, and data management. Data can easily be added to the Excel database for further processing as more weather and yield data is collected. The tool itself can easily be used by those with basic familiarity with Microsoft Office Products. The program's functionality demonstrates the potential effectiveness of utilizing weather derivatives for farming insurance and serves as a flexible and scalable tool that can generate further interest in the development of a weather derivatives program.

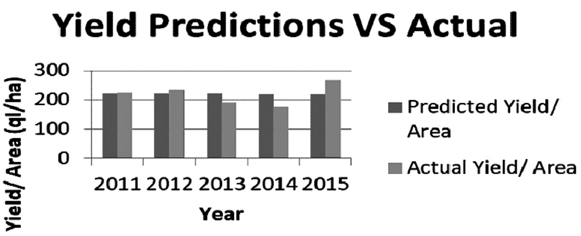


Figure 9. The accuracy of Predicted Yield Values.

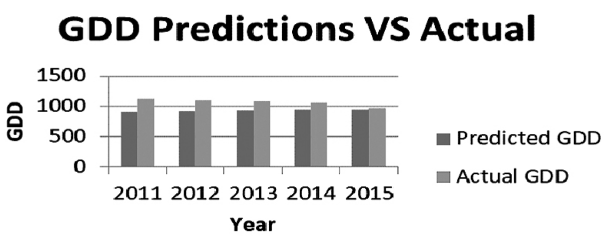


Figure 10. The accuracy of Predicted GDD Values.

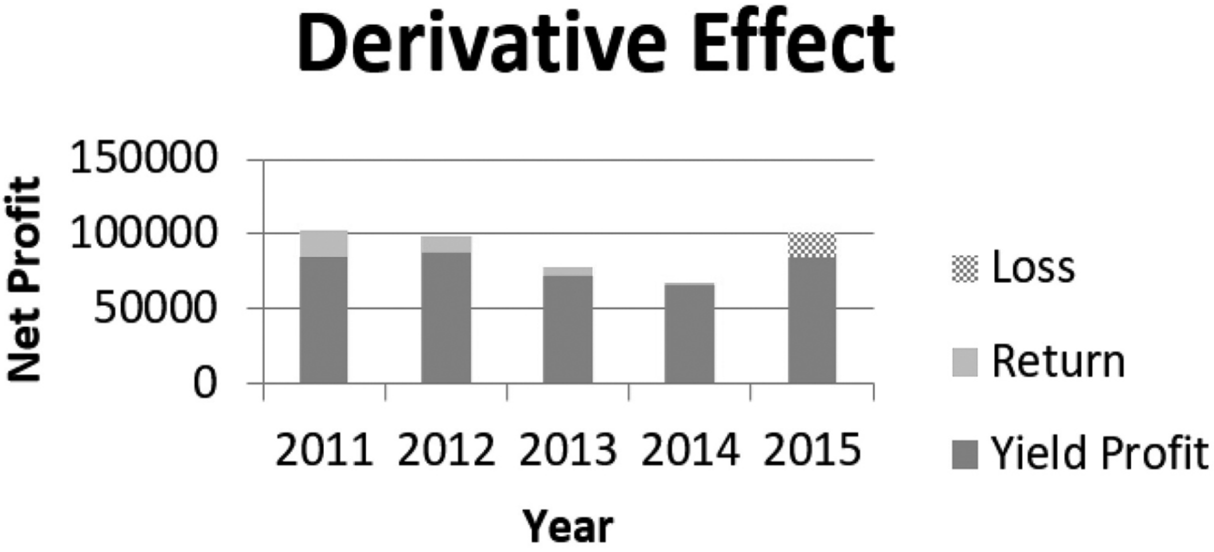


Figure 11. Profits with yield and weather derivative use.

Testing Simulation Tool

To determine the accuracy of the simulation tool and whether weather derivatives are an effective hedging tool for farmers, we added testing code to the tool. This test code takes the last 5 years of the database (years 2011–2015) and treats them as future years. For each of these years, we predict the GDD, the crop yield, and produce a derivative option. The actual yield and GDD are then compared to what was predicted to determine accuracy, and the farmer's profit is compared to the derivative return to determine its effectiveness. As each past year is tested, its information is added back into the database for the next test calculation. The results show that as more data is added to the model, it becomes more accurate (see Figure 9 & 10). It also shows that with adjustment of the tick size, weather derivatives can help considerably to cover farmer's losses (see Figure 11).

Advantages of the Simulation Tool

This simulation tool allows individuals to quickly visualize the potential benefits of utilizing weather derivatives as insurance. A farmer, or someone acting as a farmer for academic research, can input information that reflects their current economic position, and then gauge how effectively weather derivatives can mitigate their economic risks. In terms of development, it allows researchers to determine the efficiency of weather derivatives and adjust parameters as necessary when working towards a market implementation. For users, the tool's ability to easily convey the savings delivered by a derivative should generate popular interest in the product. The creation of this tool will hopefully spur the development of derivative-based insurance systems throughout Russia to further boost the agricultural sector development.

Conclusions and Recommendations

From our project work, we have compiled a list of recommendations for the further development of this weather derivative tool. Ultimately, we recommend:

Testing the tool with real users

Promoting the tool amongst real users

Conducting laboratory experiments to determine the effect of precipitation on yield and create precipitation-based derivatives

Optimizing pricing parameters

Evaluating and applying other pricing techniques

Trading the weather derivatives on a local exchange trading system (LETS)

Testing with Real Users

To confirm the effectiveness and reliability of this tool, it is imperative that actual farmers test it. These farmers would complete surveys and/or take part in focus groups to evaluate the ease of use of this tool. Additionally, these farmers can judge the robustness of the constructed models. Users would record their actual crop loss versus their predicted loss and their actual compensation from the derivatives. The differences in the actual conditions and projected conditions would then be used to create more accurate models, creating a more beneficial tool in the future.

Promoting the Tool

Once the tool has been sufficiently tested, it is important that farmers are aware that this tool exists. As described above, many Canadian farmers did not know that weather derivatives existed or how they could be utilized (Van Camp, 2015). Thus, we recommend that our tool is promoted in a marketing campaign. This promotion would involve researching the methods of communication that are most valuable to farmers (e.g. publications in an agricultural magazine, workshops like those in the India system, word-of-mouth, etc.) and then promoting through these methods. The farmers will never be aware of how this tool can help them if they are never aware of the tool itself.

Testing the Effect of Precipitation and Constructing Precipitation-based Derivatives

One issue we encountered during the development of the GDD/yield model is that, even with the preprocessing of data, cumulative GDD is not the only factor that determines crop growth. As evident in Figure 8, some years it experiences a similar GDD but vastly different yields. Precipitation also plays a key role in crop development. With global changes in precipitation patterns, it is important to factor in more than just temperature into our yield response model. Thus, we recommend conducting a laboratory experiment that analyzes the effect precipitation has on overall yield for these crops. This experiment would expose crops to the same cumulative GDD, but change the amount of water each plant receives and document each crop's growth rates. A similar experiment should also be conducted that maintains constant water levels and varies the GDDs.

Comparing the results of each of these tests would reveal which factor is more critical for the growth of different crops. A similar precipitation/yield model could be constructed so that farmers can visualize how future rainfall predictions will affect their crops. Weather derivatives based on a cumulative rainfall index can also be priced. This will allow farmers to pick between a GDD or a precipitation derivative, depending on whichever is more unpredictable and/or influential in their region.

Optimizing Pricing Parameters

Further research must be done to optimize the pricing parameters to ensure that farmers' premiums are affordable to the farmer and that these payouts provide substantial compensations. For example, the strike values of the weather derivative are currently set at 0.2 standard deviations away from the mean cumulative GDD values. By setting the strike values at a larger standard deviation away, we decrease the cost of the premium, but also decrease the likelihood of receiving a payout from the derivative. Thus, a balance must be found between the initial premium cost and meaningful levels of compensation.

Evaluating Other Pricing Methods

Finding the best methods to price weather derivatives is an open research problem. As stated before, we selected the historical burn analysis because the data needed for processing was accessible and the technique proved to be effective in previous research papers. The mathematical concepts presented were also easy to grasp and implement by our team in Excel within a limited timeframe.

Currently, more accurate methods of pricing exist, even if they were not feasible for our team to calculate. For example, Taylor and Buizza (2006) use ensemble forecasting to create their weather prediction model with data provided by the European Centre for Medium-range Weather Forecasts (ECMWF), a source which we did not have access to. With higher-fidelity forecasting models, more accurate derivative pricing will ensue and more protection will be provided to the farmers. Because weather prediction continues to be uncertain, we recommend a more comprehensive comparison of weather derivative pricing that encompasses techniques outside of those presented here. This will either affirm the accuracy of our methods or provide even more accurate pricing methods.

Trading Weather Derivatives

Most weather derivatives are currently traded on the market using over-the-counter (OTC) transactions, meaning they are not traded on formal exchange systems like NASDAQ or Dow Jones but privately negotiated between two parties (Investopedia, n.d.). We did not pursue research into bringing the derivatives to a real-world market due to lack of time for the project. Eventually, this weather derivatives system should be brought out of academia and into the real world. We recommend further research into trading derivatives on an online local exchange trading system (LETS) so that contracts can be easily bought and sold all around the world. Additionally, all derivative transactions could take place utilizing Blockchain technology (Figure 12), eliminating the need for clearing houses as well as third-party security issues. This would also decrease costs to users and increase their profits (Iansiti & Lahkani, 2017).

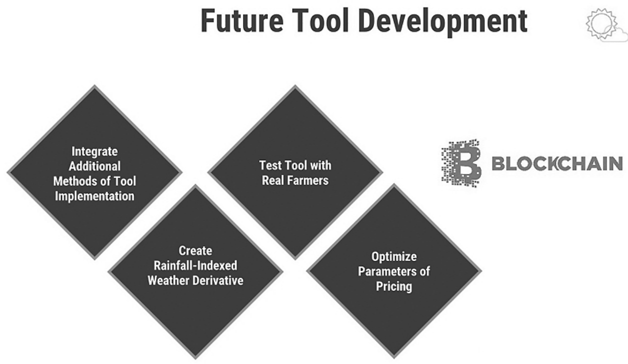


Figure 12. Further developments of the author's weather derivatives system.

Conclusion

With global climate change altering weather patterns, Russian farmers need protection from everyday weather events that will negatively affect their crop yields. This type of protection is not currently offered through traditional methods of agricultural insurance or government subsidies and furthermore, Russian farmers have a lack of faith in these products. Using weather derivatives, these farmers should be able to hedge these risks at an affordable premium price. To build a weather derivative simulation tool, our team constructed a model that demonstrates the relationship between cumulative GDD within a growing season and crop yield for corn, potatoes, and wheat in the Moscow, Krasnodar, and Omsk regions. We were then able to price weather derivatives, displaying these results and models on the Excel simulation tool. This tool can demonstrate how predicted GDDs will affect farmers' yields and how they can protect themselves from potential economic loss and thus boost popular interest in a weather derivatives system in Russia.

References

Alaton, P., Djehiche B., & Stillberger, D. (2002). On modeling and pricing weather derivatives. *Applied Mathematical Finance, 9*(1). doi:10.1080/13504860210132897.

Basic Element. (2013, December 9). The future of farming in Russia. *Farmers Weekly*. Retrieved from www.basel.ru/en/articles/farming_09_12_13.

Barrieu, P., & Scaillet, O. (2010). A primer on weather derivatives. In *Uncertainty and Environmental Decision Making: A Handbook of Research and Best Practice* (pp. 155–175). Retrieved from http://1cellonelight.com/pdf/weatherCambridge.pdf.

British Potato Council. (2006, August). *Target market report for the export of GB seed potatoes*. BPC Target Market Report Russia. Retrieved from https://potatoes.ahdb.org.uk/sites/default/files/publication_upload/BPC%20OMIS%20Report%20Russia.pdf.

Buckley, N. (2017, April). Russian agriculture flourishes amid sanctions. *Financial Times*. Retrieved from https://www.ft.com/content/422a8252–2443–11e7–8691-d5f7e0cd0a16.

Climatemp (n.d.). Omsk Weather and Temperature. Retrieved from http://www.omsk.climatemps.com.

Chung, W. (2011). Evaluating weather derivatives and crop insurance for farm production risk management in southern Minnesota. Master's thesis, University of Minnesota. Retrieved from https://conservancy.umn.edu/bitstream/handle/11299/119325/Chung_umn_0130E_12390.pdf?sequence=1&isAllowed=y.

Consedine, G. (2000). *Introduction to Weather Derivatives*. CME Group. Retrieved from https://www.cmegroup.com/trading/weather/files/WEA_intro_to_weather_der.pdf.

Country Studies. (1996). Agriculture. Country Studies. Retrieved from http://countrystudies.us/russia/60.htm.

Esper Group. (2010). NO CLIMAT but weather. *Esper Times*. Retrieved from http://www.esper-group.com/files/4/Esper-Times-_30-eng.pdf.

Glenn, J. (2017). Euro vs. US Dollar. Investor Guide. Retrieved from http://www.investorguide.com/article/15564/euro-vs-us-dollar-d1412.

Global Investment & Business Center. (2013). *Russia Regional Economic and Business Atlas* (Vol. 2). Washington, DC: International Business Publications. Retrieved from https://books.google.ru/books?id=ZEe8BQAAQBAJ&printsec=frontcover&hl=zh-CN&source=gbs_ge_summary_r&cad=0#v=onepage&q&f=false.

Groll, A., López-Cabrera, B., & Meyer-Brandis, T. (2016). A consistent two-factor model for pricing temperature derivatives. *Energy Economics, 55*, 112–126. Retrieved from http://www.sciencedirect.com/science/article/pii/S 0140988316000104.

Iansiti, M., & Lakhani, K. (2017, January–February). The truth about blockchain. *Harvard Business Review*. Retrieved from https://hbr.org/2017/01/the-truth-about-blockchain.

Investopedia. (n.d.). Over-The-Counter-OTC. Retrieved from http://www.investopedia.com/terms/o/otc.asp.

Knoema. (2015). Production and Sale of Agricultural Products, 1990–2015. Russian Agriculture Yields. Retrieved from https://knoema.com/atlas/Russian-Federation/Krasnodar-Krai/topics/Agriculture/Production-and-sales-of-agricultural-products-Gross-harvest-of-crops/Yield-of-winter-wheat.

Liefert, W. M., Serova, E., & Liefert, O. (2015). Russia's economic crisis and its agricultural and food economy. *Choices*, *30*(1), pp. 1–6. Retrieved from http://www.choicesmagazine.org/magazine/article.php?article=78.

Medetsky, A. (2016, October 6). Russia Becomes a Grain Superpower as Wheat Exports Explode. Retrieved from https://www.bloomberg.com/news/articles/2016–10–06/russia-upends-world-wheat-market-with-record-harvest-exports.

Ministry of Finance of India. (2017). *Government Sponsored Socially Oriented Insurance Schemes*. Department of Financial Services, Government of India. Retrieved from http://financialservices.gov.in/insurance/gssois/wbcis.asp?pageid=2.

Pavlova, V. N., Varcheva, S. E., Bokusheva, R., & Calanca, P. (2014). Modelling the effects of climate variability on spring wheat productivity in the steppe zone of Russia and Kazakhstan. *Ecological Modelling*, *277*, 57–67. Retrieved from http://www.sciencedirect.com/science/article/pii/S 030438001400057X.

RIHMI-WDC, Russia, CDIAC, USA. Daily Data. Air Temperature and Precipitation. (n.d.). Retrieved from http://meteo.ru/data/162-temperature-precipitation#доступ-к-данным.

Simmons, S. R., Oelke, E. A., & Anderson, P. M. (1985). *Growth and Development Guide for Spring Wheat*. St. Paul, MN: University of Minnesota Agricultural Extension Service. Retrieved from https://conservancy.umn.edu/handle/11299/165834.

State's executives of the Krasnodar Region. (n.d.). *Agricultural of Krasnodar Region*. Retrieved from https://www.krasnodar.ru/en/content/453/show/32845.

Sun, B., & van Kooten, G. (2015). Financial weather derivatives for corn production in Northern China: A comparison of pricing methods. *Journal of Empirical Finance*, *32*, 201–209. Retrieved from http://www.sciencedirect.com/science/article/pii/S 0927539815000328.

Taylor, J., & Buizza, R. (2006). Density forecasting for weather derivative pricing. *International Journal of Forecasting*, *22*, 29–42. Retrieved from http://www.sciencedirect.com/science/article/pii/S 0169207005000634.

Ukhova, D. (2013, September). After the Drought: The 2012 Drought, Russian farmers, and the challenges to adapting to extreme weather events. Oxfam Case Study. Retrieved from https://www.oxfam.org/sites/www.oxfam.org/files/cs-russia-drought-adaptation-270913-en.pdf.

van Camp, M. (2015). Weather derivatives to mitigate weather risk to crops. Country Guide [Paragraph 3, 4 and 5]. Retrieved from https://www.countryguide.ca/2015/11/23/weather-derivatives-to-mitigate-weather-risk-to-crops/47647.

Acknowledgements

Our team would like to thank the following individuals for their contributions to the completion of our project:
Worcester Polytechnic Institute and The Financial University under the Government of the Russian Federation for providing us with the means and opportunity to complete this project.
Alexander Ilyinsky, Dean of the International Finance Department at the Financial University, for his guidance and for planning the foundations of the project as our sponsor.
Tatiana Goroshnikova, Deputy Dean of the International Finance Department at the Financial University, for her weekly advice and guidance.
Svetlana Chugunova for organizing our stay and accommodations while in Russia.
Oleg Pavlov, Stephan Sturm, Gbetonmasse Somasse, Michael Radzicki, Michael Johnson, and Anton Losev, for sharing the knowledge of their respective fields during our interviews and team meetings.
Svetlana Nikitina for coordinating with The Financial University under the Government of the Russian Federation to make this project possible and for her continual guidance throughout the project as our advisor.

About the authors

Eric Carkin, student of Robotic and Electrical engineering at WPI, ecarkin@gmail.com
Stanislav Chekirov, student of International Finance Faculty at Financial University, chekirovstas@gmail.com or 142195@edu.fa.ru
Anastasia Echimova, student of International Finance Faculty at Financial University, echimova.anastasia@gmail.com or 164615@fa.ru
Caroline Johnston, student of Mathematical Sciences major and Computer Science minor at WPI, Ceej39@gmail.com or cmjohnston@wpi.edu
Congshan 'Shannon' Li, student of Architecture Engineering and Mechanical Engineering minor at WPI, Shan1143148746@gmail.com or Cli8@wpi.edu
Vladislav Secrieru, student of International Finance Faculty at Financial University, vlasec08@gmail.com or 144077@edu.fa.ru
Alyona Strelnikova, student of International Finance Faculty at the Financial University, lkastrelnikova@gmail.com or gimnaz23@kubannet.ru
Marshall Trier, student of Robotic engineering at WPI, Marshalltrier@gmail.com or mtrier@wpi.edu
Vladislav Trubnikov, student of International Finance Faculty at Financial University, WolveVlad@gmail.com or unclelad777@mail.ru

Appendix

Appendix A. Relevant Equations

A Growing Degree Day (GDD) is defined as

$$GDD_{i,n,c} := \frac{T_{max,i,n} + T_{min,i,n}}{2} - T_c ,$$

where $T_{max,i,n}$ and $T_{min,i,n}$ are the maximum and minimum recorded temperatures, respectively, for day, i and year, n; and T_c is the base temperature for crop, c.

Cumulative GDD is defined as

$$\sum_{i=s}^{q} GDD_{i,n,c},$$

where s and q are the start and end dates of the growing season, respectively.

The expected payout for a weather derivative with low GDD or high GDD is defined as

$$E_{p,LOW} = D\sigma\left[\phi(n) + n\Phi(n)\right]$$

$$\text{or } E_{p,HIGH} = D\sigma\left[\phi(m) - m + m\Phi(m)\right],$$

where D is the tick size (dollar value per unit of GDD), μ is the mean value of GDD's, σ is the standard deviation of the GDD's, ϕ is the PDF of the standard normal distribution, Φ is the CDF of the standard normal distribution, and

$$n := \frac{K_1 - \mu}{\sigma},\ m := \frac{K_2 - \mu}{\sigma},$$

where K_1 is the strike value for the low GDD value, and K_2 is the strike value for the high GDD value (see Sun and van Kooten (2015) for derivation). The dollar is used as the choice of currency in the tick size because of its historic stability (Glenn, 2017). Thus, the price or payout of an option will not fluctuate due to inflation.

The price (premium) of the option is defined as

$$c = e^{-r(u-v)} E_p,$$

where c is the premium that hedgers pay for the contract, r is a risk-free periodic market interest rate, v is the date that contract was issued/purchased, and u is the date the contract was claimed/expiration date. E_p is the expected payoff based on predicted or historic mean value of temperatures (see Sun and van Kooten for the derivation).

The actual payout is defined as,

$$p(x)_{farmer} = \begin{cases} D(K_1 - x),\ x \le K_1 \\ 0, K_1 < x < K_2 \\ D(x - K_2),\ x \ge K_2 \end{cases},$$

where x is the realized cumulative GDD.

In a historic burn analysis, the expected payout is set equal to the average historical weather conditions. In the case of GDD, it is defined as

$$\mu := \frac{\sum_{j=1}^{n} \sum_{i=s}^{q} GDD_{i,j,c}}{n}.$$

In the derivative tool, the interest rate, contract length, risk loading factor, and m and n values were fixed. Additional information (including a downloadable version of the tool) can be found on our website at https://sites.google.com/view/russiaweatherderivatives/home?authuser=0

Погодные деривативы в России: страхование фермеров от колебаний температуры

Eric Carkin[1], Станислав Чекиров[2], Анастасия Екимова[2], Caroline Johnston[1], Congshan Li[1], Vladislav Secrieru[2], Алена Стрельникова[2], Marshall Trier[1], Владислав Трубников[2]

Этот проект предлагает использовать погодные деривативы — тип финансового инструмента с выплатой на основе погодных условий — как метод для российских фермеров для подстраховки от ежедневных колебаний температуры. Мы создали инструмент моделирования производных погоды в Microsoft Excel, который вычисляет влияние температуры на урожайность, а затем анализирует, как возврат производных погоды может потенциально компенсировать потерю урожая. На основе этого инструмента мы разработали ряд рекомендаций, которые помогут внедрить эту систему защиты реальными пользователями.
Ключевые слова: производные погоды; колебания температуры; хеджирование; потери урожая
JEL classification: G13, G17, Q18

[1] Worcester Polytechnic Institute, MA, USA
[2] Финансовый университет, Москва, Россия