ABSTRACT

Climate Change is causing extreme weather events, such as drought, to become more frequent and severe, which causes increasing losses in the Kansas Wheat industry. A four-step model, primarily consisting of a multiplayer perception, was created to predict future losses for wheat in Kansas until 2050. The outputs of the model showed that losses are projected to increase the most in the Spring Season, 70% from 2020 to 2050, led by Drought, Hail, and Frost. This leads to recommendations for the implementation of till farming, hail nets, row covers to reduce the severity of these specific climate risks.

Deep-Learning Analysis of Extreme Climate Events to Predict Future Losses for Wheat in Kansas

Jacob Rintamaki

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Executive Summary

5.2% of the US economy is agriculture-based, and one of the largest grain-based crops in the US is Wheat. Kansas is the number one grower and exporter of Wheat in the US, but increasing climate volatility from Extreme Climate events caused by climate change, such as drought, has led to an increase in crop losses. This project focuses on utilizing a deep learning model, which is excellent at dealing with multivariate (high-dimensional) data to predict how the Wheat crop losses in Kansas will change over the next 30 years.

I primarily used two data sources: The USDA Risk Management Agency Cause of Loss Files and the US Global Research Program 2017 Special Climate Report. I used the Cause of Loss files to collect my historical Extreme Climate Variable and Wheat Loss data, while the 2017 Special Climate Report was used to predict future trends for the Extreme Climate Variables because it had the data for how temperature and precipitation values were going to change.

The methodology for this project can be broken up into four parts, as follows: The monthly indemnity and causes of loss for extreme events that cause over $50,000 in loss are taken from the USDA Cause of Loss Files and used to create a multilayer perceptron framework for my model. Next, Exploratory Factor Analysis (EFA) was performed on my eleven climate variables, resulting in 4 principal components being calculated, which were then used to group my 11 extreme climate variables to better predict the future trends for these variables until 2050. Variable-specific trends from the 2017 Special Climate Report are added to my EFA-created groups to create a set of my future extreme climate variable values. The future climate variables are then fed into my model to output my predicted results, in millions of dollars of Wheat crop loss.

The best fit for the initial model was a normal topology, which had an estimated MSE of around 109.6896 (+/- 10.47 million dollar range) and the best bias-variance tradeoff for most epochs. The results from the final model show that Drought and High Precipitation events (such as hail) are the driving causes of these increases and that Spring is the season with the most indemnity and the highest rate of increases (4.4 million dollars/year, non-inflation adjusted) for Wheat Losses over the next 30 years.

Based on my model, I identified three areas of risk: Kansas Farmers + Sub-Groups, Agricultural Industry, and Foreign Nations. Kansas Farmers + Sub-Groups primarily have the risk of outlier years from Drought and Hail events, which can be even more damaging for low-income and minority farmers. The Agricultural Industry has the challenge of potential layoffs due to changes in Wheat pricing from losses, and Foreign nations that are reliant on American exports may have the danger of economic turmoil if heavy losses occur to Kansas Wheat over the next 30 years.

The bulk of the recommendations focuses on addressing the growing risks from extreme climate variables in the spring season, primarily with Drought, Hail, and Frost by advocating for the implementation of minimum tillage, hail nets, and row covers, respectively, in areas where their relatively high price for materials would be able to offset increased climate risk. I also recommended progressive federal legislation such as the Green New Deal and joining international climate plans to help deal with the risks to the Kansas Agricultural Industry and the Global Economy, respectively.

Background Information

5.2%, or $1.109 trillion, of the US economy, is agriculture-based. Of that $1.109 trillion, $136.1 billion of that is created directly from US-based farms, but that amount is magnified due to a large number of codependent organizations and industries that surround farming, such as food and beverage stores. [1] 13.0% and 10.9% of US expenditures and jobs, respectively, also are related to agriculture, making it one of the most vital economic aspects of the US. [1]

Of this industry, one of the largest grain-based crops is wheat [2], which names the state of Kansas as its largest producer [3,4,5]. Kansas produces around 18.68% of the US wheat supply in 2017 [4], which amounts to 467 million bushels of wheat, which helps to contribute to wheat's status as a top-3 crop, due to its demand for grain-based products such as cereal, pasta, pizza, or other processed foods.

Since wheat is so important for the economy of Kansas, it's vital to understand the optimal conditions for the growth of this crop, because it could lead to better modeling practices. Wheat needs 12 to 15 inches (31 to 38 centimeters) of water to produce a good crop, and it grows best when temperatures are warm, from 70° to 75° F (21° to 24° C), but not too hot. Wheat also needs a lot of sunshine, especially when the grains are filling. [6] All of these factors point towards wheat growing the best in a relatively mild environment without too many extremes, whether in terms of drought, precipitation, temperature, or other variables.

All of the variables that I just mentioned could be classified as climate variables that have the potential to change in the coming years because of the phenomena of climate change. Climate change, also known as global warming, is the tendency towards more unusual and sporadic weather conditions around the globe due to a multitude of factors, but primarily from carbon and hydrocarbon emissions, such as carbon dioxide and methane. There are numerous examples of how climate change could impact the environment, agriculture, cities, almost every aspect of human existence, but one thing that they have in common is that most climate studies tend to focus on gradual changes to big variables. [38]

The focus of many climate studies is on how temperature, precipitation, or other gradual events will change over time, rather than the more sporadic extreme events that are projected to grow dramatically due to climate change. While there is still research about this area, I feel that it is underrepresented when it comes to agricultural modeling. [39]

Including extreme weather events for agricultural modeling could strengthen how people will handle recommendations to help respond to climate change because of human psychology since one of the problems that climate activists often face is that it can be hard to sway other people's minds without concrete problems that can be addressed at the moment, rather than hypotheticals in the future (even if they are highly likely to occur). [40]

The applications of machine learning to these problems are becoming increasingly common as well, due to the recent advancements in AI education. One paper that deals with the applications of machine learning to modeling agricultural losses [7] showed that Deep learning was able to outperform traditional regression and statistical models when it came to predicting agricultural losses, but that it was heavily reliant on the robustness and stability of the model, along with the amount of type of data used, which can be challenging due to the not always standardized nature of agricultural data collection.

As Climate Change advances there must be a comprehensive analysis and predictions of how climate change and agriculture losses are related in the state of Kansas for the Wheat crop because faulty or non-existant actuarial modeling could lead to millions of dollars of wasted insurance dollars if done incorrectly.

Data Methodology

For this project, I primarily drew from two data sets: The USDA and the US Global Change 2017 Special Climate report. The information from these data sets let me specifically gain data about how extreme climate events were changing in Kansas, how the agriculture industry for wheat was changing in terms of losses in various forms. A climate model was utilized for my future climate based predictions rather than having excessive historical climate data because historical climate data is proving to be less reliable due to the increasingly dramatic shifts in the Earth's climate [41], but I still utilized historical data (primarily for my indemnities) to set a baseline for my model's predictions. Below are detailed overviews of the two data sets that were utilized in this project, and it includes the scopes and parameters as well as the purpose for the usage for these particular data sets.

<u>USDA RMA Cause of Loss (Primary Data Set)[8]</u>

Scope and Parameters: Monthly indemnity data for wheat for Kansas from 2003 to 2020 from the USDA Risk Management Agency's "Cause of Loss Files". I also used data from this database to determine the type and number of losses over $50,000 from each defined "category" of loss.

Purpose of Data: This database fits into four data categories: Defining Frequency, Defining Severity, Separating outcomes into different variables, and defining historical trends. The ability for me to see how the total amount of monthly indemnity has changed over the last 18 years, which is under defining historical trends and defining severity, while seeing the number of extreme events for each variable over the last 18 years fell under defining the frequency of these events while separating my extreme events into multiple variables, rather than just a generalization. The type and number of losses over $50,000 from each defined "category" of loss also fit into defining the severity (over $50,000) and frequency (# of times that an extreme event occurred) for creating my initial model.

Data Pre-Processing and Cleaning: I used the IF() function in MS Excel to determine how many climate events in my datasets caused losses of over $50,000 before using a pivot table to filter out my data according to time (year and month), state, and crop. I used my 18 years of data from 2003 to 2020 to create a full raw dataset that I would later use for my models and analysis. To prevent NaN (not a number, represented by a blank tile in Excel) values, I used the Excel function ISNUMBER() to find gaps in my extreme climate data to fill in with 0s.

Factor Selection: I originally started with 23 factors (different causes for extreme climate events), but I decided to narrow that down to 14 primary factors by using the SUM() Excel formula to determine if the event occurred at least once per year (sum >=18), because if it were too infrequent, then it would be classified as an outlier. The loss function that my initial model uses (which I plan to discuss in further detail at a later point), mean squared error, is very susceptible to outliers, so I got rid of these 9 factors (23 to 14 variables) to create a more coherent model. Besides, since my model focuses on climate variables, some of the causes of loss were not directly related to climate, so I had to further cut down my climate variables to a total of 11 variables listed below: Cold Wet Weather (CWW), Cold Winter (CW), Drought (DT), Excess Moisture/Precipitation/Rain (EMPR), Flood (FD), Freeze (FZ), Frost (FR), Hail (HL), Heat (HT), Hot Wind (HW), Wind/Excess Wind (WD)

Data Reliability: The data source is federally provided, on a .gov website, and has been commonly used for commercial and policy-related purposes, so I feel that despite any formatting issues I might encounter that it is a trustworthy source. The large amounts of zero values in the dataset, however, do slightly decrease the effectiveness of the data source, but that is a more minor flaw compared to the rest of the prior reasons stated for determining data reliability.

U.S. Global Change Research Program 2017 Special Climate Report (Secondary Data Source)[9]

Scope and Parameters: I took data relating to the potential rise in temperature, precipitation, and drought risk for the Midwest Region (Including Kansas) from chapters 4-9 of the report.

Purpose of Data: I choose to use this data primarily for making future predictions and modeling my eleven extreme climate variables. The severity of my extreme climate events was kept constant, so using this database to find how the frequency of these events was predicted to change over time was critical for my modeling efforts.

Data Reliability: These predictions from the data are accurate because not only was this federally commissioned and made up of a team of climate scientists, but it had to pass through six stages of peer review edits, making it an appropriate and stable choice for climate forecasts.

Mathematics Methodology and Analysis

Methodology Step 1: Model Framework

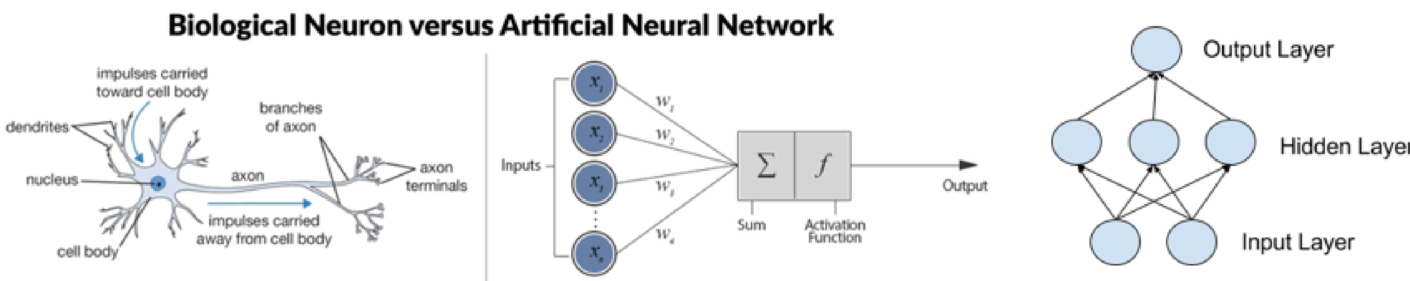
Model Framework Introduction:

To understand how my eleven extreme climate variables and monthly indemnity are related, I created a multilayer perceptron model to analyze my USDA RMA dataset.

Model Framework Background:

To later set up my future model that would do the forecasting, I needed to create a framework to understand how my indemnity (wheat losses) and my eleven extreme climate variables are related. My initial model is called a multilayer perceptron deep learning model, and it functions similarly to a human brain, where inputs are sent to neurons, which cause an output to occur. That's what happens in a humans brain, but in computer terms, my model takes in inputs (my 11 extreme climate variables), assigns weights to them and adds biases (similar to linear regression depending on how important each variable is), and then send them through an activation function which maps my linear regression onto a nonlinear function. All of these steps are important because they can account for any shape for a function that would adequately fit my data.

Figure 4.10: Basic Framework of an Artificial and Deep Neural Network



The figure above, figure 4.10 [10], is what makes up a neuron for a deep learning model, and these neurons can come together to form topologies or the shape of my model. In the 2nd image to the figure (figure 4.10) [11], there are three layers, an input layer, a hidden layer, and an output layer, each of which plays an important role. The input layer takes in the climate data, the hidden layer transforms these inputs using linear and nonlinear functions, then the output layer provides a final transformation before giving the result. Where this model stands out is in its learning process. This model can become more accurate by comparing its results to what the value is supposed to be, a process known as supervised learning, where a loss function of the difference between the value outputted by the model and the "correct" answer is attempted to be minimized. The lower the loss, the more accurate the model. To decrease this loss, the model then uses a process called backpropagation, which systematically adjusts the weights and biases of each of the neurons to try and decrease this loss function to its global minimum, which is the lowest point on the function. A common loss function is called Mean-Squared Error (MSE) and is widely used because it has just one extrema point (which is always a minimum) that makes it easy for a backpropagation algorithm to work with.

<u>Model Framework Assumptions</u>

*1.This model only analyzes wheat crops in Kansas***.** Kansas is the #1 producer of wheat in the US, so it is a relevant crop that also has the potential to be dramatically affected by extreme climate events. I also wanted to narrow down my topic so that I can create a targeted model that could make relevant predictions rather than a broader and less relevant model.

2.Only insured farms are measured. My model uses the USDA's information on crop losses for the historic crop losses, so there is no data on uninsured farms. Besides, since a core component of my recommendations is related to an insurance policy, that would not apply to uninsured farms.

3. I can help to prevent overfitting in my model by utilizing batches, Train/Test splits and analyzing my model's learning curves for different topologies. Due to the relatively smaller amount of data that my model is trained off on, overfitting is a common risk. Batches are a method in Keras where the dataset is processed in chunks rather than all at once to save memory and to avoid over or under-fitting. I choose to use batches because one of the problems with having sparse data (due to the nature of extreme climate events not occurring daily) is that underfitting or overfitting can occur very easily, so using batches can help to properly fit my model. Train/Test splits (specifically 67/33 for my model) can help to reduce overfitting because, ideally, the training results and the test results for MSE should be similar. If there is a point where a disconnect occurs, and the values for MSE don't match up (A term called variance in the machine learning world), then the model is at risk for overfitting. My final technique for preventing overfitting is the analysis of my models' learning curves for different topologies because the addition of more nodes or more hidden layers can potentially lead to lower values for the loss function. This isn't always the case, so analyzing this is necessary to avoid incorrect assumptions.

<u>Model Framework Implementation</u>

Every machine learning model is built differently, and I wanted to describe three of my choices about my model framework that were chosen to optimize its results and minimize potential pitfalls. I used an assortment of data science libraries in python (notably Keras, Scikit-Learn, and Pandas) with a TensorFlow (deep-learning library) backend to complete the learning for my model because each of these three data science libraries has built-in functions for creating models that make it easy to document and explain while TensorFlow has the computational complexity to properly compile and run my models. These libraries also have the capabilities for random starting seeds, which are important to utilize because they can keep the results of each topology constant across multiple iterations, which is important for repeatability. I used ReLU (Rectified Linear Unit) as my activation function for my model because, since it follows the form $f(x) = max\,(0, x)$, not every neuron is activated during backpropagation, so it makes my algorithm much more computationally efficient. I used the ADAM optimization function in my model because it can adjust the learning rate to prevent the two problems that come from having a fixed learning rate: Bouncing and slowness. If the fixed learning rate is too large, then while the model might make great steps at first in its backpropagation, it will be difficult for the model to pinpoint a minimum. If the fixed learning rate is too small, then the earlier problem I mentioned won't occur, but the model will be extremely inefficient in trying to calculate the minimum for the loss function. ADAM takes larger steps at the beginning and then transitions to smaller steps to accurately find the minimum of the loss function efficiently, making it the ideal choice for my model.

Model Framework Results and Analysis

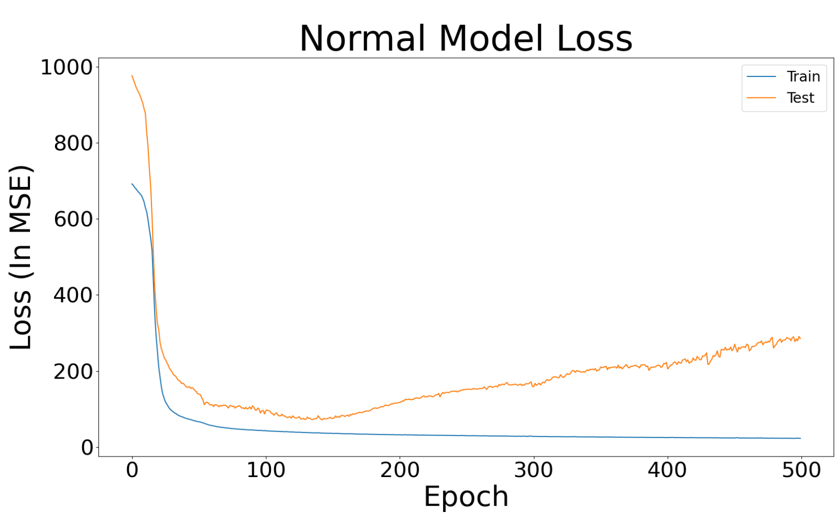
The results for my Model Framework are not in dollars, such as how the final output of this project will be, but rather in Mean Squared Error (MSE). Mean squared error is the average of the squares of the difference between the expected and actual values of a model, so if a model had an MSE of 100 units^2, then it would be (on average) off between +/- 10 units. For each of the three topologies (normal (1 hidden layer), wider (1 hidden layer but twice the neurons), deep (2 hidden layers)) that I studied, I created learning curves to show how the MSE of the models changed as the number of epochs (the number of iterations of my model) increased, and I found some interesting results that can best be explained by the machine learning concepts of the Bias-Variance tradeoff. [13]

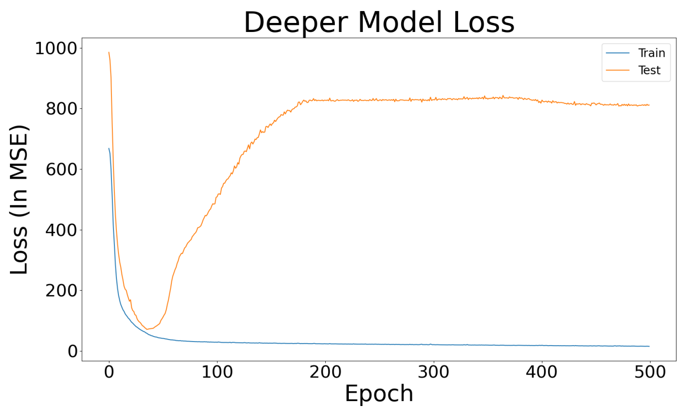
Bias is a measure of how "off" the model is from actual results (characterized by MSE), while variance doesn't refer to statistical variance, but rather how well the model can generalize its results. If the model has a high variance, then it is too focused on training data and doesn't perform well on testing data. Below I show the Train/Test learning curves (Figure 4.12) [12] for each of the three topologies that I analyzed, and the importance of the Bias-Variance tradeoff will shortly be made apparent.

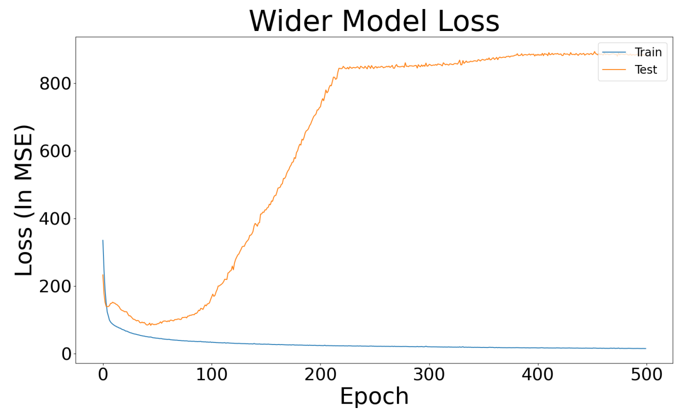
The first key feature to analyze is the inflection point that occurs in every testing function, which occurs at the 40/50 epoch mark for the wider and deeper models (respectively), and the 150 epoch mark for the normal model. I hypothesize that this mismatch in testing and training curves is due to overfitting [14] of the data after a specific epoch mark due to the relatively low amount of data and the large presence of zero values in my dataset, which can cause the vanishing gradient effect. [15] The vanishing gradient effect refers to how the gradients for specific variables that repeatedly show as zero get multiplied across multiple layers, which causes them to not be activated, which is an issue for less frequent Extreme Climate Variables. I was able to mostly avoid it with my ReLU activation function, but it can be apparent after hundreds of epochs due to the nature of my dataset it appears.

I chose to focus on the Normal Model from the epoch range 0-150 as the framework for my MLP model because it not only has the lowest MSE at that epoch, but it has the best bias-variance tradeoff for the most epochs among the three topologies. While there is a better bias-variance tradeoff for the Deeper Model near the beginning, its sharp inflection indicates instability, while the gentler slope and inflection point of the normal model tends to indicate stability. Despite the three learning curve charts being essential for determining the strength of my model, I also conducted a test (Figure 4.13) where I used my model's normal framework to predict values for Wheat loss given the historical data, and then I plotted these two curves against each other to see how well they overlapped.

Figure 4.12: Initial Model Topology Results

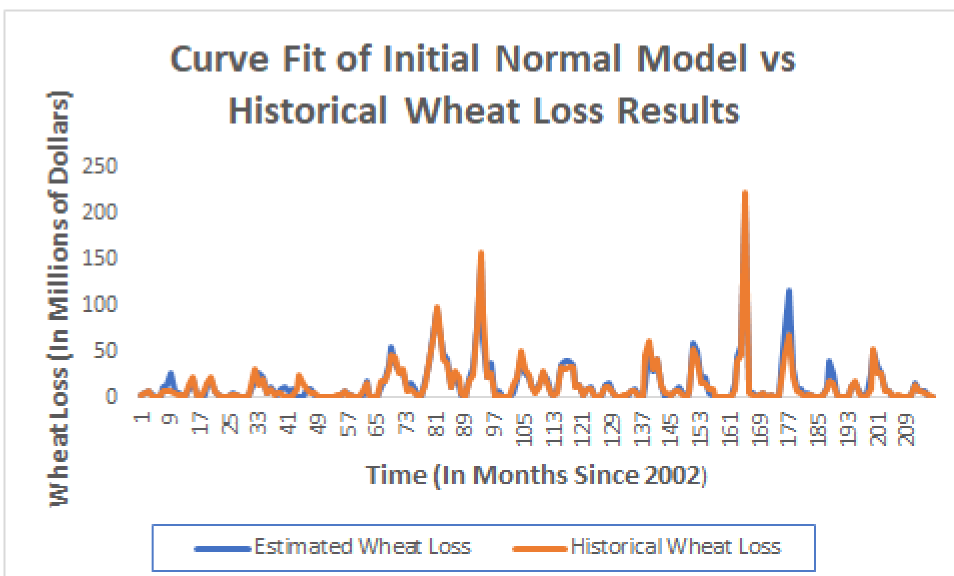






The Mean Squared Error of my Normal Model Loss was 109.6896 (Equivalent to +/- 10.47 million dollars), which is quite a good fit because, as seen from the two curves below, the difference between the estimated and actual historical wheat values tended to be towards zero for most instances, and was only brought up by specific spikes, which is more frequently due to underestimation rather than overestimation. I also feel that the curve fit of my model is a more accurate predictor than MSE for the overall health of my model because MSE can be dramatically affected by outlier events, while the curve fit allows for a broader picture about my model's performance.

Figure 4.13: Initial vs Historical Results



<u>Model Framework Conclusion</u>

The "Normal" Topology (1 Hidden layer) proved to have the best bias-variance tradeoff, and I used it to make the framework for my overall model. This choice was then justified by the high degree of curve fit between my historical indemnity data and the Normal Topology model.

Methodology Step 2: Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis Introduction:

In my model framework, I took extreme climate data from the USDA dataset without considering that there might be underlying relationships between the variables. Exploratory Factor Analysis (EFA) is a mathematical technique that will let me group up my 11 extreme climate variables into fewer groups so that it can be easier to predict their future values and one of the first steps of EFA is Principal Component Analysis (PCA).

Exploratory Factor Analysis Methodology:

PCA is a statistical method used to analyze the relationships between variables to try and reduce the dimensionality (number of variables) of a dataset so that it's easier to understand.

The first step of PCA is to standardize each of my variables to have a mean of 0 and a standard deviation of one because PCA is very sensitive to how my data is scaled, especially since a large portion of my data is made up of 0s. I then created a correlation Matrix, A, by calculating the correlation between each of my factors using the CORR() function in RealStatistics, which is described by the formula to the left. I then computed the eigenvalues of Matrix A and then sorted the eigenvectors for each eigenvalue in decreasing order. To pick the right number of principal components to accurately explain my data, I used the Kaiser Criterion: the number of principal components that have an eigenvector > 1 will be used. This resulted in 4 components being chosen (2.447,1.729,1.473,1.303), which are PC1, PC2, PC3, and PC4. All of the eigenvalues can be seen in the figure below (Figure 4.2) which is called a scree plot, and the variance explained was calculated by dividing the eigenvalue of each component by 11 (the sum of all eigenvalues and my number of variables) to get a percentage. This plot helps to justify my choice of 4 eigenvalues because after the first four none of the other components explain more than 10% of the variance. I can then create a transformation matrix W with the eigenvectors as columns to compute the new principal components as follows: $Y = W^T * X$

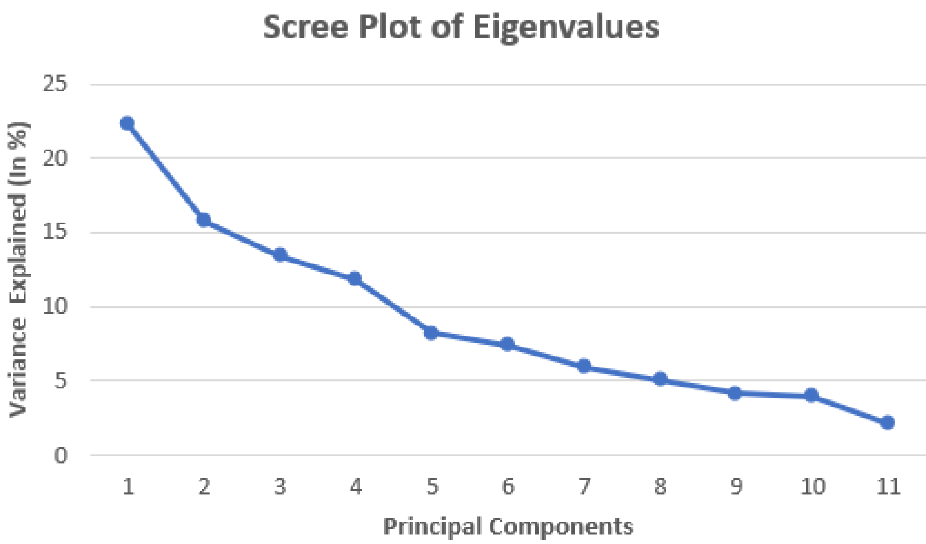
The results of my PCA show that my four uncorrelated principal components can account for 22.25 + 15.73 + 13.39 + 11.85 = 63.21% of my model's variance. Although many of my extreme climate variables have multiple causes, the results from my PCA seem to show that the 2nd component was related purely to precipitation, the 3rd component was primarily related to temperature (because of the Freeze), and that the 4th component was a combination of precipitation and temperature. Since temperature and precipitation appear to be major driving causes in all of my components, this is important to keep in mind for future risks and recommendations to the Kansas area, especially in the public policy area for both the State and Federal levels. An important note to consider is that although four of my factor loadings are above 1, which normally shouldn't happen, this can be explained due to the extremely wide variance in Extreme Climate events that can occur that is still apparent even when the data is fully standardized.

Despite the relatively lower total variance from my principal components, which can be justified due to the inherent volatility of both extreme climate events and climate-based models in general, I feel that it justifies my factor selection because I could describe almost 2/3rds of my model's variance with less than ½ as many components as variables (4 components vs 11 variables). The groupings by the component that I gained from this analysis will be used in the next section to help sort my variables into specific groups so that their future trends can be more easily ascertained.

Exploratory Factor Analysis Conclusion

I was able to group up my original 11 Extreme Climate Variables into 4 groups, corresponding to General Uncertainty, Precipitation-Based, Temperature-Based, and Mixed, respectively, which will help me to create trendlines for my extreme climate variables in my next methodology step.

Figure 4.2: Scree Plot, Principal Components, and Variances



Variable	PC1	PC2	PC3	PC4
Cold Wet Weather	-0.432	-0.427	-0.0630	**-0.544**
Cold Winter	-0.347	-0.214	-0.377	**4.00819**
Drought	-0.316	0.0111	0.697	**-1.315**
Excess Moisture/Precipitation/Rain	0.103	**-0.553**	0.294	0.434
Flood	-0.158	**-0.948**	0.167	0.267
Freeze	-0.0876	0.616	**1.123**	-0.507
Frost	0.0449	0.292	-0.131	**-0.3320**
Hail	-0.295	-0.319	0.595	**1.401**
Heat	0.190	0.255	0.733	**-0.960**
Hot Wind	-0.107	0.209	0.126	**-0.488**
Wind/Excess Wind	0.163	0.185	**0.447**	-0.00881
PC Variance	**22.25%**	**15.73%**	**13.39%**	**11.85%**

<u>Methodology Step 3: Future Extreme Climate Variables</u>

<u>Future Extreme Climate Variables Introduction:</u>

My overall model works by outputting wheat loss as a function of extreme climate variables, but to predict future values of wheat loss, I also need future values for my extreme climate variables. For a more traditional agricultural model, which is built off of average climate values, there are pre-made predictions, but because I am using extreme climate variables, I have to create my trends.

<u>Future Extreme Climate Variables Assumptions</u>

1. Averages were used for predictions, which may give a higher overall indemnity than just using mode or median values due to the large range of values. I chose to use averages during my forecasting because it could help to provide a realistic assessment rather than a too low or a too-high assessment (which can be later accounted for with confidence intervals).

<u>Future Extreme Climate Variables Implementations</u>

To calculate future values for each of my climate variables, I first split up my raw data into four seasons (Spring, Summar, Winter, Fall). I then found the means for each of my variables for each season using the AVERAGE() function and then multiplied this number by the percentage growth or decline in frequency that the 2017 Climate Science Report predicted. (Ex. If a 25% increase occurred, then I would multiply the average by 1.25). I then subtracted my original mean from the climate variable to get the change in frequency over the next 30 years, and I then divided this number by 30 to get the annual change in frequency for each of my variables. I then used this to create a linear regression trend for each of my variables, which gave me four datasets that I later combined into one using the SORT() MS Excel function.

<u>Future Extreme Climate Variables Results [16]</u>

Table 4.3: Future Extreme Climate Variables Relative Change (In %)

Variable Name	CWW	CW	Drought	Frost	Hail	Heat	HW	EMPR	Flood	Freeze	W/EW
Change (In %)	(+) 18.75	(-) 5	(+) 10	(-) 5	(+) 25	(+) 5	(+) 5	(+) 25	(+) 25	(-) 5	(+/-) 0

I split up my results for my future extreme climate variables into the four seasons because although the growth or decline for each variable was given on an annual basis (as shown in Table 4.3 below), having the highest growth rate doesn't make a variable the most important. (Ex. 10 * 1.25 < 100 * 1.01) The values for the table in Table 4.3 were found in the 2017 Climate Special Report projections for 2050, where extreme temperature highs are expected to increase by 5% (leading to an increase in heat-based events and a decrease in cold-based events) and Drought is expected to increase by 10%. Extreme Precipitation is expected to increase by 25%, CWW was calculated as a combination of heat and precipitation (0.95 * 1.25 = 1.1875), and there are no projected values for wind, so I kept that constant. A more in-depth analysis of the actual changes will occur in the risks and recommendations section of this paper.

<u>Future Extreme Climate Variables Conclusion</u>

Precipitation is expected to increase by 25%, Droughts by 10%, Hot Temperature by 5%, and Colder temperatures are expected to decrease by 10%. I used combinations of these increases to help predict future values for my 11 variables off of my previous groups determined by EFA, and I plan to plug these values into my future framework in the next methodology step below.

Methodology Step 4: Future Framework Predictions

Future Framework Predictions Introduction:

For my future model, I utilized the future extreme climate variable data that I gained from my previous 2 models into my original initial model to make seasonal indemnity predictions for wheat farmers in Kansas.

Future Framework Predictions Assumptions

1. The results of this model will be seasonal (traditional 3-month grouping) rather than monthly or annual (Sum of indemnities in the months in a given season). The problem with monthly or annual data is that it often isn't as practical for farmers and others in the agricultural industry, because their timelines of planting, growing, and harvesting are on a seasonal basis, not a yearly. For this model, the months for each season are: Winter = December 1st - February 28th (or 29th), Spring = March 1st - May 30th, Summer = June 1st - August 31st, Fall = September 1st - November 30th

2. Inflation will not be included in this model. While Inflation certainly is a factor for any monetary-based model, especially since the rate of US Inflation is predicted to be around 2% per year, I decided not to include inflation in my model because it is not directly related to my extreme climate variables and I feel that it would lead the reader to draw skewed conclusions about my future model results.

Future Model Implementation [20]

I first ran my future deep learning program in python to generate the predicted loss values for each of my seasonal inputs, but I then copied that data over into an MS Excel worksheet for better data control. I then took this newfound list and split it up into five sections: Overall, Spring, Summer, Fall, and Winter using the SORT() function. I then calculated the mean and standard deviations for each of my sections to find the 95th percentile confidence interval for each of my graphs, because that could help with showcasing the uncertainty in my model more accurately. I found my confidence intervals with the MS Excel formula CONFIDENCE.NORM(0.05, STDEV, COUNT()), where the 0.05 refers to 1 - alpha = 0.95 for 95th percentile confidence interval. To make the upper and lower limits, I added my confidence term to the value for the upper limit and subtracted the confidence term to the value for the lower limit. To plot the confidence intervals, I just set the upper and lower limits as area graphs, set the color of the lower limit to white, and then set the color of the upper limit to a translucent blue to help visualize the uncertainty in my model.

Future Deep Learning Model Results

The results for the future deep learning model, projected for every season over the next 30 years (along with each season) are pictured in the figure below (figure 4.3).

A noticeable trend that occurs in the lower graph is the periodic nature of the wheat loss curve, which shows three of the seasons (Summer, Fall, Winter) more tightly grouped at the lower ends of the Wheat loss spectrum, while Spring is consistently higher than all of them. This increase in spring's loss is also growing at a faster rate than the other three seasons, indicated by the vertical stretching of the graph in later years.

The predicted losses for the four individual seasons all follow linear trendlines, which is to be expected, as they are a combination of multiple linear trends from the previous Extreme Climate Variable regressions. The slopes of the seasons, (Spring, Summer, Fall, Winter, respectively), are 4.42, 1.29, 0.78, 0.83. These slopes (Wheat Loss/Time (In Years)) represent how the Wheat Loss is expected to change for each year since 2020, and it shows that although each of the seasons is expected to experience more loss in the future, Spring losses are expected to grow at a significantly higher rate than the other three seasons. A final overview of my model (Table 4.4) is given below, which could potentially be of use to future researchers or analysts.

Figure 4.3: Overall and Seasonal Wheat Loss vs Time over 30 Years

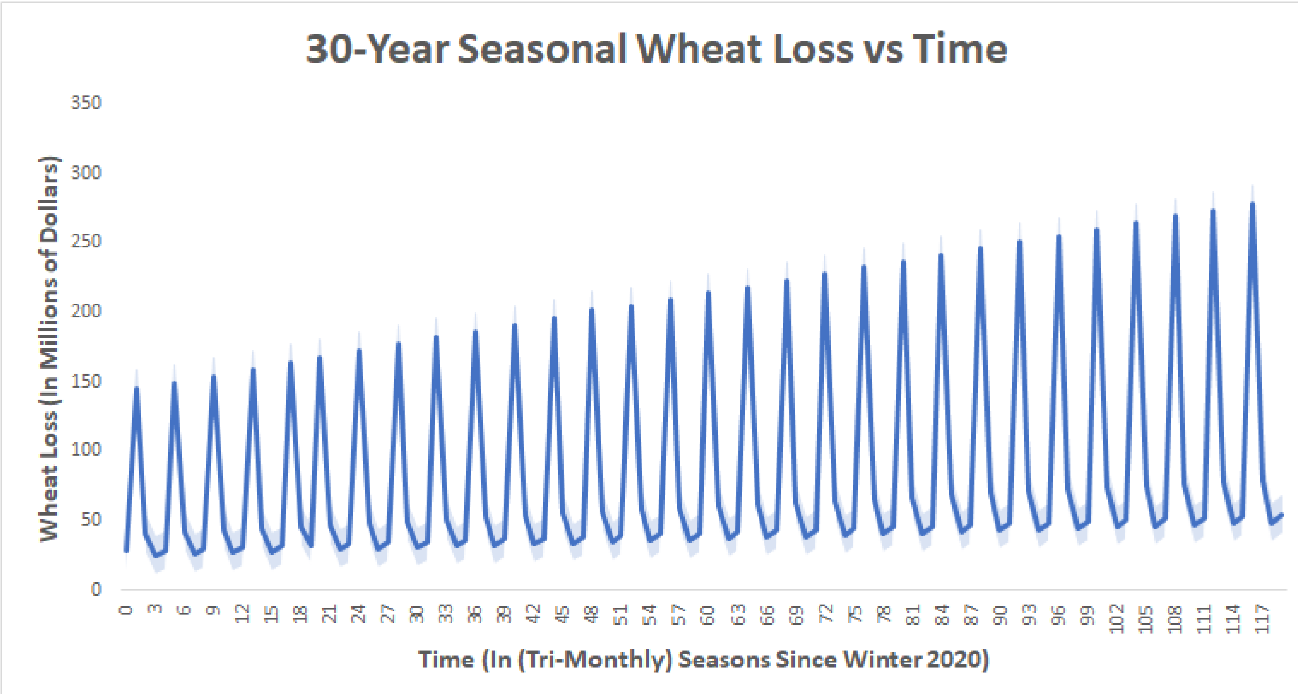


Table 4.4: Future Model Strengths and Weaknesses

Item	S/W	Why?
Relatively Low Error on "Higher" losses	Strength	"Higher" losses tend to be harder to predict due to their inherent variability, so this is a good sign of a strong model
Best approximated with "normal" model	Strength	Less model complexity and less memory/run-time
Activation, Loss, and Optimization Functions/Algorithms	Strength	Since these are already well-chosen, the model format itself is less of a concern, and the data is more of the weak point for further improvement
More Error on "Lower" losses	Weakness	Since the confidence interval was the same throughout, this would naturally have a greater impact on the "lower" losses because it was a greater percentage of change relative to their means.
Less Data than traditionally expected	Weakness	Can lead to overfitting, as seen from the learning curves in Part 1

<u>Future Framework Conclusion</u>

The future framework predicted that the Spring season would have the highest potential losses and the highest rate of increase in losses out of all the seasons, but that losses in every season were also predicted to increase as well

<u>**Risks and Recommendations**</u>

Risks

Risks Introduction

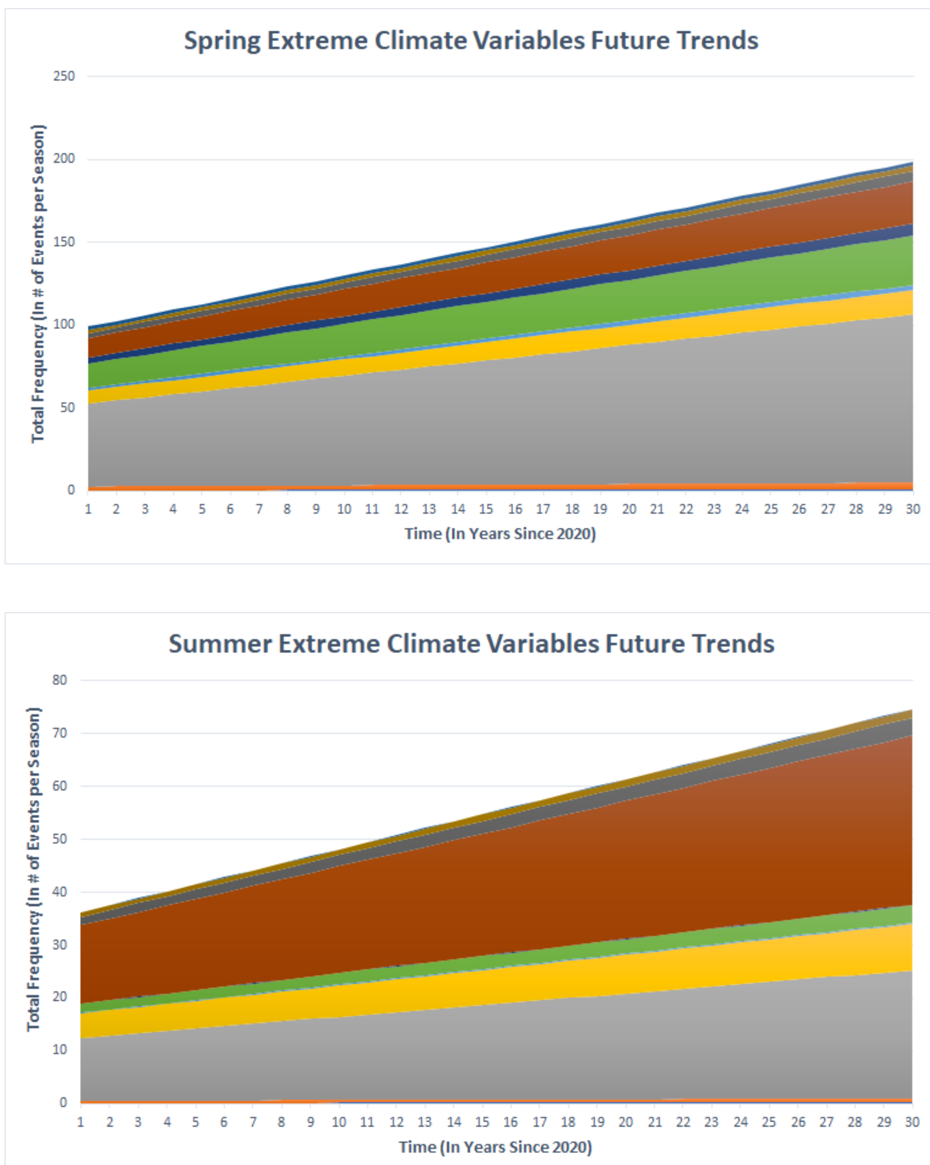
The persons affected by the potential increases in Kansas Wheat losses who could benefit the most from the results of my model can be split up into three groups: Kansas Farmers and Sub-Groups, the Kansas Agricultural Industry, and the Global Economy.

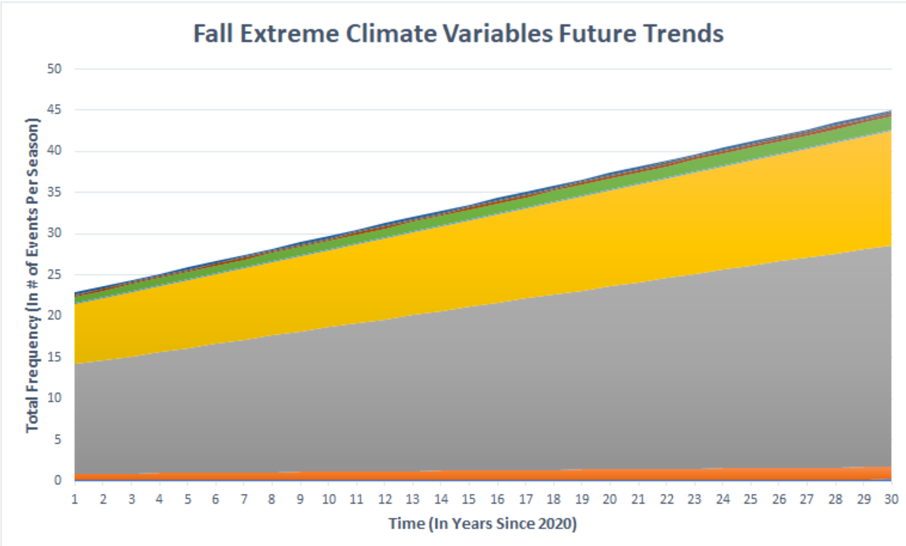
Kansas Farmers and Sub-Groups Seasonal Risk Characterization

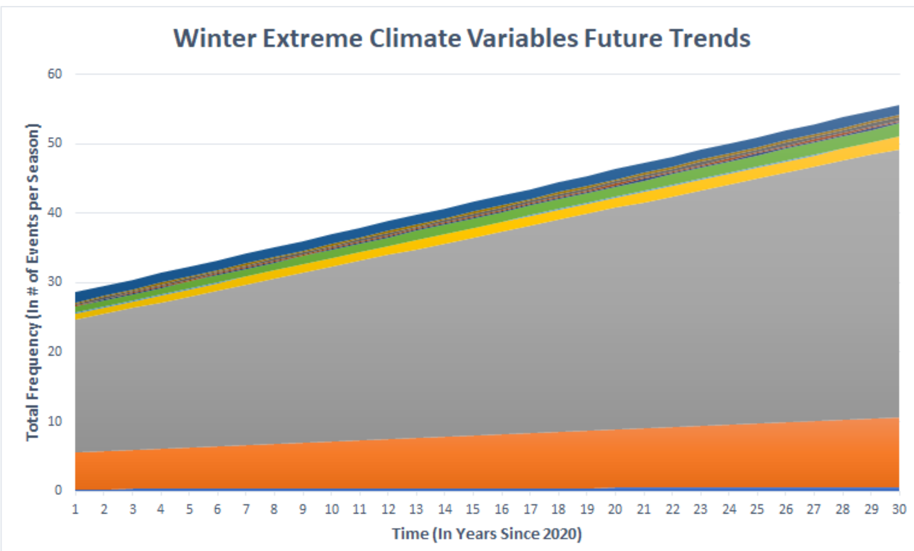
Figure 5.1.1: Legend for Figure 5.1

The legend for Figure 5.1 is to the right, as indicated by Figure 5.1.1, and in addition to this legend, it should be noted that although the four seasons are juxtaposed next to each other, their scaling is not equal.

Figure 5.1: Expected Change in Average between 2003-2020 to 2050 [14]







The spring season for wheat in Kansas contains the highest total frequency for extreme climate events that cause losses over $50,000, which can be attributed to the fact that Wheat's initial growing season takes place during these months, making it more susceptible to losses than a seed or a mature plant would be. Despite the multiple variables in this graph, three trends are vital to discuss. 1.) Drought was and remains the largest component for total frequency, which means that it should be given the most important when it comes to later modeling risks and recommendations. 2.) Freeze losses are the primary measure of temperature-based damage because Wheat is sensitive to low temperatures in some of its earlier stages of development, which makes sense. 3.) Excess Moisture/Precipitation/Rain and Hail do not appear to have a significantly larger share of the total frequency, but floods noticeably are, meaning that although drought is more likely to cause severe losses, that floods could also become a factor. While this may seem to juxtapose at first, floods and droughts both increasing make sense because the variability in precipitation is what is driving these events. The total amount of precipitation is not necessarily dramatically changing [16], but the distribution of that precipitation in large bouts vs none at all is shifting towards the extreme ends rather than the bountiful center.

The Summer season in Kansas has a noticeably lower total frequency for extreme climate events that cause losses over $50,000, primarily because the Wheat crops are generally more developed, but there are still important trends and items to discuss. The first item that comes to mind is the relative lack of heat-based losses because while these do increase from Spring, they aren't at the levels that one would assume to expect. Kansas has a relatively mild summer climate, temperature-wise, compared to many southern agricultural states such as Georgia, which means that Wheat will generally not suffer many temperature-based losses because it generally can thrive up until 28C (82.4F) [17], while the average high for Kansas in the summer is around 81F [18]. The second item that I wanted to discuss was that precipitation, whether in excess or a lack of it, was the largest, 2nd largest, and 3rd largest causes for loss in the summer, with Hail being a larger issue than Drought.

The fall season has the smallest total frequency of extreme climate events that cause losses over $50,000, which can be attributed to Wheat being harvested and planted more frequently in the spring and summer months. The only noticeable trend to take the importance of is that precipitation, in the primary form of drought and the secondary form of Excess Moisture/Precipitation/Rain dominates losses in this season, which is important to keep in mind.

The winter season has the second smallest total frequency of extreme climate events that cause losses over $50,000, but not the smallest, which can be attributed to the growth of "Winter Wheat", [19] which can take advantage of the high levels of fall precipitation to grow in Kansas. Drought is the overwhelmingly largest cause of extreme climate events that cause losses over $50,000, but Cold Winter is the 2nd largest cause, which makes sense due to Cold Winter most likely being common in Winter. There are not many losses due to extremely high levels of precipitation though, unlike the other seasons, which is something that should be noted.

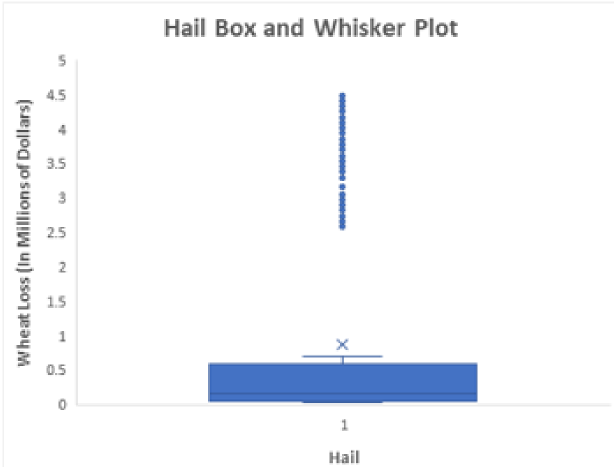
As shown from the previous final model results, future wheat losses for Kansas farmers are projected to increase in every season from 2020 to 2050, but the rate and causes for these increases are different for every season. Despite the numerous risks that are apparent to farmers in multiple seasons, the most pressing concern is the Spring season, which has the highest Total Frequency and expected future losses for Wheat, so the majority of the Risks Analysis will be focused on the Spring Season.

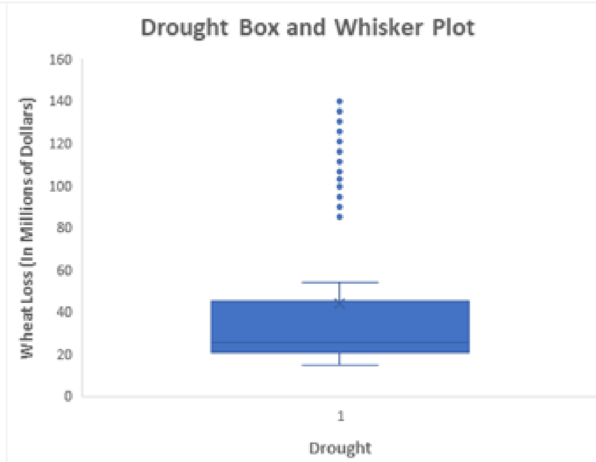
The Spring season has three primary Extreme Climate Variables that make up around 2/3rds (Relatively constant from 0.66-0.67) of the total frequency for Extreme Climate variables despite being 3/11 of the variables. The three variables are Drought, Hail, and Frost, and below I show three box and whisker plot diagrams which describe the losses by each Extreme Climate Variable changes between for 2050.

The 3 charts in the figure (Figure 5.2) shown below all have a common trend that the uppermost deviations are more prominent than the lowermost deviations, showing that while the median and interquartile values tend to be lower, there is the potential for extremely high outliers in most instances. The Drought and the Hail Box and Whisker plots demonstrate this, because their maximum points are significantly higher than even their quartile ranges, showing that there is a great potential for high outlier events to occur for these variables, which is common with precipitation-based events. The Frost Box Plot and whisker, however, don't share these outliers, which can be attributed to the less extreme forms of temperature-based events, as their damage tends to be more gradual.

Included in this figure are the descriptive statistics of these three variables, which should help to further show the data that went into maxing the box and whisker plot diagrams above.

Figure 5.2: Descriptive Statistics and Boxplots for Drought, Hail, and Frost for 2050





Statistic Type	Drought	Hail	Frost
Minimum	14.406	0.0255	0
Q1	21.001	0.0495	0.127
Median	25.706	0.163	0.429
Q3	40.165	0.519	1.989
Maximum	142.254	4.49	4.729
Mean	43.708	0.872	1.311
Range	127.847	4.465	4.729

Despite the focus on the Spring season for Wheat losses in Kansas, there is still an important factor that makes the other three seasons vital to analyze, and that is due to their higher volatility in loss amounts. The confidence interval around the Summer, Fall, and Winter seasons is a larger percentage of their mean than the Spring Season, so this can make predicting the exact value of a season's loss more difficult. One [21] of the largest risks to farmers in Kansas is a sub-group of farmers, specifically lower-income and minority farmers. These groups are more susceptible to heavy increases in losses to Wheat due to climate change because many simply do not have the scale to shrug off losses or the excess funds to pay both insurance fees and ride out heavy loss years. This is not a trend that is unique to Kansas however, because low-income and minority farmers across the US [22] increasingly are being outcompeted by larger farms and corporations, so the losses detailed above from Drought and Heavy precipitation are compounded for these groups.

Agricultural Industry Risk Characterization

The Kansas Agriculture Industry, defined as the collection of farmworkers and small food or wheat-related business owners in this instance, has two prominent risks that could severely damage it. The first risk relates to Kansas farm workers because an increase in losses year over year to farms could lead to workers being laid off or having their pay cut to prevent the farm from going under, which is more likely to be common in smaller, low-income farms. An example of this would be if losses increased by 10%, but the farmers couldn't raise their prices, then their expenses would have to be slashed to break even, and their workers would be likely to get laid off. Similarly to this, losses could affect the health of small food or wheat-related businesses in Kansas if the price of wheat increases from a drop in supply due to heavy losses, because then their expenses would have to go up to stay in business, which could drive them into potential bankruptcy.

Foreign Nations (Global Economy) Risk Characterization

The US is the number 2 exporter of wheat worldwide by quantity, and since Kansas is the number 1 producer of wheat for the US, this means that Kansas has a disproportionately large influence on the global wheat exportation market. The three previous categories of risks that I mentioned (Regional, agricultural groups, and sub-groups) have the potential to compound any changes in Kansas wheat farming to the US's trading partners around the world, one of which is the Philippines. Right now the Philippines is the largest receiver of wheat from the US, [23] with a 12% quantity increase from 2019 to 2020, and 95% of it's wheat supply comes from US-based importation. While agriculture is still a significant portion of their economy, it has not been without challenges. The rise of climate change and other socioeconomic factors in the Philippines have lead to some challenges with self-sufficiency when it comes to the outside food supply in some areas in food, [24] so if Kansas begins having a severe increase in losses, then this could hurt the economies of not only the Philippines but the many other countries who might rely on the US for wheat.

Risks Conclusion

Most of the risks came from the Spring season due to its high level of crop losses from Drought and Precipitation-Based extreme climate variables, but the risks of the losses from these major Springtime events also pose issues to both the Kansas Agricultural Industry and the Global Economy due to Kansas's position as a top exporter of wheat.

Recommendations

Recommendations Introduction

The risks that I have previously mentioned to the three groups: Kansas Farmers and Sub-Groups, Agricultural Industry, and Foreign Nations (Global Economy) are all varied and cannot be accounted for by a singular overreaching recommendation.

Kansas Farmers and Sub-Groups

Spring is the greatest season for Wheat losses over the next 30 years, so the first recommendation that I could give would be to start increasing the premiums for insurance across the state of Kansas because the increase in losses isn't going to be going away anytime soon. Since the slope of the linear regression for Spring losses is 4.42, this means that the overall total amount of money paid to insurance in the state of Kansas should be increasing by about 4.42 million dollars every year to keep pace with the increase in average losses, not adjusted for inflation. During the spring, the three main Extreme Climate Variables that make up 2/3rds of the loss are Drought, Hail, and Frost, and I have separate recommendations for farmers to help mitigate the risks for all three of these Extreme Climate Variables by modifying their outcomes.

To help mitigate the risk of drought, I recommend that minimum tillage should be employed throughout the state of Kansas.[25] Minimum tillage is a type of farming technique that doesn't till the earth as much, letting the soil remain relatively untouched, and it has been shown to have great benefits. Minimum tillage has been shown to reduce the water usage for crops by 50% relative to normal tillage, making it effective for dealing with droughts, but one of the only problems with this method is that it can take time for farmers and their crops to adapt to this style, so it may require more educational training and less expensive long-term subsidies to encourage participation. Besides, since soil infiltration is increased from minimum tillage it could also help to mitigate floods since the water would be able to drain into the soil more rather than staying on the surface as runoff.

To help mitigate the risk of hail, I recommend that hail nets should become more widely used throughout the state of Kansas. [26] Hail nets are large swaths of PP or HDPE netting that are suspended over the crop it's protecting to shield it from hailstorms. They are generally effective in preventing damage from hail storms, but they are also quite expensive at around 0.10-0.25$/square meter covered.Therefore, rather than having them being implemented at every single farm area in Kansas, I recommend that they first be distributed to farmers in the highest areas of risk to maximize the benefit for each tax dollar spent, rather than areas that don't suffer the brunt of hail damage.

To help mitigate the risk of Frost, I recommend that row covers could be implemented throughout the state of Kansas. [27] Row covers are strips of cloth that are laid over the soil to help retain heat, and this could be vital for reducing frost damage in the spring because while extreme frosts that are below 0F are often unavoidable, the smaller frosts of around 32F can be mitigated if the soil is even kept a few degrees warmer from row covers. Row covers can cost around $1/square meter, however, which could make lower income farmers less likely to buy them, but I believe that this could be solved in part by the ARC and PLC programs, mentioned below.

I mentioned in my risks section that low-income and minority farmers had greater levels of risk relative to larger farmers when it came to dealing with losses, so one of the programs (which was partially implemented as part of the 2018 Farm Bill) was the USDA Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) programs. [30] These two programs, run by the same organization that created the causes of loss files for the wheat database, are increasingly being utilized by low-income and minority farmers to help prevent them from going out of business due to increasingly catastrophic years. Increasing the awareness about these programs, along with making concerted efforts to push underrepresented groups into applying for these programs, could help to protect some of the more vulnerable farming groups in Kansas.

Agricultural Industry

Despite the policy changes that should be implemented for Kansas agricultural workers and business owners, there are three critical pieces of legislation in various stages and support in the US Congress that could help to address some of the fundamental problems surrounding agriculture today. The first piece of legislation that I recommend is the Agriculture Resilience Act, proposed by Maine Congresswoman Chellie Pingree, [32] which has the goal of reaching a net-zero emissions standard from US Agriculture by 2040. Pingree mentions the Extreme Weather Patterns being caused by climate change that poses a risk to farmers in the US, which aligns with my report, and how we need to be proactive to keep farmers in business while losses are rising. Agricultural Activities contribute 8.4% of the total US Greenhouse Gas emissions, so following this plan, which is comprised of 6 concrete and science-based areas (Research, Soil Health, Farmland, Pasture-Based Livestock, On-Farm Energy, and Food Waste), is a reputable Act that could potentially open the doors to the more drastic changes needed to curtail Climate Change in our society.

One of these drastic changes, which has received a high level of controversy over the last 2 years, is the Green New Deal, proposed by New York Representative Alexandria Ocasio-Cortez [33] and Senator Edward J. Markey of Massachusetts. The Deal itself is modeled after FDR's New Deal plan, which was an economic reconstruction of America during the Great Depression, and it is a sweeping resolution, with an estimated price of between $10 to $93 trillion, [34] but many experts argue that the benefits could outweigh the costs in the end. The Deal itself has numerous proposals, which would not become laws even if it were passed, but the majority focus on the goal of cutting US Carbon Emissions to 0% by 2050. While there are undoubtedly numerous items in this Deal that could be beneficial to both the Agricultural and Climate Aspects of this report, there is one major reason why I am not fully recommending this Deal: Chance of passing. The Deal is incredibly controversial among the conservative wing of American politics, and there is even hesitancy among the Democratic party for passing this piece of legislation, for fear that it would cause their approval ratings to sink. Unless there is a bipartisan agreement or a left-leaning supermajority (in case of a filibuster attempt), this Deal will most likely not pass in its current form, so it must not be focused on as much as the next and final piece of legislation, the Farm Bill.

The Farm Bill could be argued as the most critical piece of periodic Agricultural Legislation in the American government, as it is remade every 5 years, and because of this, is the best opportunity to have an immediate impact based on these recommendations. The Bill itself, “starting during the 1930s as part of President Franklin Delano Roosevelt’s New Deal legislation, Its three original goals – to keep food prices fair for farmers and consumers, ensure an adequate food supply, and protect and sustain the country’s vital natural resources – responded to the economic and environmental crises of the Great Depression and the Dust Bowl. While the farm bill has changed in the last 70 years, its primary goals are the same.” [35] The Bill is remade every 5 years as it goes through both the Senate and the House of Representatives, and unlike the Agriculture Resilience Act or the Green New Deal, this Bill is almost 100% guaranteed to pass in 2023 when it expires again, so it is the best opportunity to start implementing agricultural policies based on climate and actuarial science.

Foreign Nations (Global Economy)

Finding a way to help reduce foreign nations' dependency on the US for wheat exports is vital for mitigating the potential economic effects of a catastrophic year for Wheat losses. A paper by the FDCL, an organization partnered with the UN, found that there were two [36] methods for reducing this reliance on foreign exports that appeared to have worked in multiple case studies across the globe: Support for domestic production, and the restoration of sovereignty over trade flows. Supporting domestic production refers to local governments supporting small-scale farming and the development of local infrastructure to start planting more crops, rather than outsourcing to large corporations, since this is often more sustainable and conducive to the economic well-being of the nation. The restoration of sovereignty over trade flows refers to strengthening the protections for smaller or importing countries when entering trade deals or dealing with foreign investors to ensure that they can have control over their agricultural industries, rather than being forced into an unfair position due to economic needs.

In addition to slowly ending the dependency on America for wheat exports, the other half of this problem has to deal with climate change. One of the largest global plans to tackle climate change is the Paris Agreement, [37] which is a long-term climate plan signed by 196 countries to reduce global warming to a maximum of + 2 (preferably 1.5) Celsius. Despite this monumental agreement, there have been concerns that it won’t be strong enough to bind countries to reduce their carbon emissions worldwide, because if an option isn’t economical then it will be harder to pursue, so the idea of a carbon tax has been put forward as an alternative option. A carbon tax is a tax on any carbon emissions, to penalize unclean energy or manufacturing practices that may be accelerating climate change. [38] Carbon taxes are seen as a controversial topic because their effect on national economies hasn’t been fully explored yet, but the theory is plausible.

Recommendations Conclusion

The bulk of the recommendations focuses on addressing the growing risks from extreme climate variables in the spring season, primarily with Drought, Hail, and Frost by minimum tillage, hail nets, and row covers, respectively, but I also recommended policymaking and joining international climate plans to help deal with the risks to the Kansas Agricultural Industry and the Global Economy.

Conclusion

The purpose of this project was to create a model for predicting future losses to Wheat crops in Kansas, and it has fulfilled this purpose due to its high level of fit, low MSE, and statistical analysis results as shown in prior sections.

From the results of this project, I have learned that future projects should make sure that the datasets being used should be checked for both NaN values and file type to ensure that there aren't mismatches, along with increasing the total amount of data because that could help to decrease the MSE even more than what I have shown here.

Future uses for this project are outlined in the previous recommendations section, but this work can be translatable to the renewable energy forecasting field, as it is very closely related to climate data, especially for photovoltaics.

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Appendix

The anaconda deep learning environment with a CPU, not a GPU, on a Dell Laptop, was utilized, with the pathway Users\Rintamaki\Desktop\Jake’s stuff\modeling python [filename].py.txt

The statistical and data science python program versions that I used were: Scipy: 1.4.1, numpy: 1.19.2, matplotlib: 3.3.2, pandas: 1.1.5, statsmodels: 0.12.1, sklearn: 0.23.2

The deep learning programs versions that I used were: Theano: 1.0.4, Tensorflow: 2.2.0, Keras: 2.4.3

Code can be found in this google document file, which has influences from [11] (link sharing included): https://docs.google.com/document/d/1cb0IziZ-Mmy0yBDZjQoYeafVhOt07ikBc6ygaIF0kmQ/edit?usp=sharing