Analysis of Global Feed Grains Consumption

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1 Abstract

In the industry of producing animal feed crops, there is a problem of controlling fluctuating prices. In the world market, the demand for animal feed crops is increasing every year. The management and production challenges are increasing due to changing weather conditions and the increasing production costs. This study focuses on analyzing the consumption trends of animal feed crops and the factors affecting prices by considering geography, years, and commodity types.

For the study process, this research uses data from the USDA, checking for outliers, and categorizing data. In addition, descriptive statistics and correlation analysis were used to find the relationship between various variables such as grain prices, production volume, and market changes. The analysis results show that factors such as location and year have a significant impact on grain prices. It is likely that in the future, the demand for grain in the world market will continue to increase, but production will decrease due to climate change, which has a direct impact on the economy in developing countries in terms of import and export taxes.

This study will be very useful for the agricultural industry in analyzing the factors that directly affect production and demand trends in the global market. In the future, the results of the study can be applied to develop more efficient management practices for animal feed crops, as well as design policies that reduce the economic and environmental impacts of grain production and trade. The industry can use this information as a basis for decision-making to increase productivity and reduce operating costs more effectively.

2 Introduction and Background

2.1 Introduction

In 2012, the United States experienced a series of severe weather events, in particular a prolonged drought that affected a variety of feed crops [40]. Consequently, food products that relied on feed crops, such as meat and dairy, increased dramatically in price [31]. This predicament is not solely an isolated incident in the United States, it has been observed across the globe on multiple occasions. Feed crop shortages occurred from 2007 to 2008 in both third and first-world countries [18]. A growing number of critics are pointing to the increased demand for feed crops, particularly wheat and corn, to be used as bio-fuels as the cause of the crisis [28][49]. More recently, the 2022 conflict involving Ukraine and Russia has led to a spike in essential feed crop prices worldwide [47]. Sometimes, feed crop shortages are not caused by external factors outside a country's control, but occur due to poor internal budgeting. For example, in the early 2000s, Zimbabwe failed to import sufficient feed crops, and the nation's livestock population suffered dramatically [19]. Predicting future feed crop necessary supplies would prevent such famines from occurring, as it would allow farmers to adjust agricultural yields or governments to import feed crops ahead of time. This is particularly important for industrializing countries, which have historically been shown unable to modernize their agriculture fast enough to meet feed crop demand. These nations should instead rely on purchasing large amounts of feed crop imports to close the gap [42].

2.2 Background

The animal feed industry has grown significantly in the past decades, especially the industry of animal feeds using grains [3, 16, 53]. Over the past century, the world's food consumption trends have changed dramatically, and the number of calories most people consume per day has increased worldwide [3, 11, 29]. The consumption trends are increasingly focused on meat, vegetable oils and sugar [53]. Developed countries tend to consume meat and dairy products, while developing countries mainly consume grains and roots [29]. However, the consumption of legumes and tubers has declined significantly in many regions [29]. The increasing demand for meat over time has led to fluctuations in the grain and animal husbandry industries, as well as global supply and demand prices [16].

Factors affecting the expansion of the animal feed grain industry include the increase in the world population, which is projected to continue to grow to 9.15 billion by 2050 [12], and the increasing demand for meat in developing countries, especially in Asia [11, 29]. By 2050, the demand for animal feed grains is projected to increase by another 35% as the demand for animal protein increases [36, 39], resulting in higher demand for grains; and the growth of global trade and economics, which has led to the support of more diversified grain production, such as maize, wheat, oats, barley and sorghum [15, 17, 41]. Major producers and consumers include the United States, China, Brazil, and the European Union [17]. Many countries have, therefore, developed food and bio energy policies to support rural farmers [49], which has an impact on grain pricing and market volatility worldwide [20, 42].

Corn is the world's largest grain, with over one billion metric tons grown annually [17]. As a grain that can be used as food for both animals and humans, it can also be used as a raw material for renewable energy or bioenergy [35]. Other globally important grains are wheat, which is a staple food in many countries [15], and oats, which are grains with high nutritional value [41]. The production of grains is not only for animal feed but also for providing energy to humans [44]. Today, many people are starting to see the importance of whole grains, which are very useful in treating chronic diseases and reducing premature death rates [32].

However, even though farmers are able to produce a large amount of grain each year, they face many challenges that directly impact the industry and the global environment [22]. Climate change is one of the problems farmers faces [43]. For example, droughts affect C3 crops such as rice and wheat, as higher temperatures reduce yields [43]. However, C4 crops such as maize, sorghum, and millet benefit from droughts, as they are generally more tolerant of heat [43]. In addition, changes in water levels affect the uptake of nutrients by plants, as too much water can deprive the roots of oxygen [43]. Therefore, areas at high latitudes and in the tropics are more likely to be affected than others, which can lead to significant reductions in agricultural yields and increased planting times [43].

In addition to climate change, emissions have a direct impact on global warming, with about 50% of animal feed production contributing to greenhouse gas emissions [25]. For example, the use of nitrogen fertilizers produces nitrous oxide, the fermentation in the digestive tract of cows produces methane, and the fermentation of grass and soybeans increases the production of carbon dioxide [2, 25]. The three largest carbon footprint crops are rice, wheat, and corn, respectively [56]. The United States, Canada, and India have higher carbon footprints than any other country [15, 17]. Farmers can reduce their greenhouse gas emissions by, for example, returning stubble to the soil, which absorbs 41-90% of carbon, or practicing no-till farming, which can reduce emissions from soil by up to 10% [56]. Some countries, such as the United States and Japan, have implemented carbon labeling policies to help consumers make environmentally friendly choices [56]. China is also looking at ways to reduce its carbon footprint [56].

Modern farmers are becoming aware of the problems that affect the environment and the global economy. Therefore, they are introducing technology into their crop production [10]. For example, machine learning is used to sort out seed materials such as minerals, coffee beans, grains, gravel, and tablets, using ANN technology to detect differences in materials and analyze their movement [33]. Discrete Element Method (DEM) simulations show that when adding noise variables, the accuracy decreases, but the efficiency is still acceptable [33]. Some farmers have used deep learning to predict agricultural product prices from weather and environmental data [54]. The test results show that the LSTM-CNN model for 5, 10, and 15 weeks in advance is more accurate than the predictions made by experts in the lab [54]. In addition, deep learning and U-NET can be applied to screen the quality of grains such as lentils and pixie beans to predict the percentage of seed weight effectively and help reduce conflicts between traders and farmers from different grain quality assessment standards [5]. Another example is the use of Random Forest to predict the specific density, electrical conductivity, and starch production of each corn seed in real-time [45], and the use of CNN to classify oat subspecies [41].

The future trend is expected to increase the production of grains for animal feed and consumption [52]. Although the United States is the center of the global food system and has import tariff disputes from many countries [20], international organizations such as the WTO should be involved by pushing for policies to reduce export tariffs and agricultural industry tariffs and promote fair competition in the global market [4]. In addition, foreign direct investment (FDI) policies should be regulated to support food security [53]. In the 21st century, the global demand for food and animals will double, and crops will be used for bioenergy [49]. The development of new genetic technologies and biofuels will help reduce the impacts of global warming and natural disasters [49]. When the demand for consumption increases, one of the factors that should be considered is the health of animals [8]. Farmers should also pay attention to the problems of parasites and diseases that are hidden in animals [8]. The future trend is that the development of Genetically Modified Crops or genetically modified crops will increase from the original and be accepted by many countries [21, 30]. Another problem that may be encountered in the future is the limitation of natural resources [22]. If farmers want to expand their cultivation area, they may have to deal with limited land and water [46]. Agricultural products that are expected to grow higher are the vegetable oil and soybean markets [46]. Livestock prices may be volatile in developing countries [46]. However, people can access agricultural products more easily from the National Online Agricultural Market (e-NAM) [48]. In the future, it is expected that business models suitable for small farms will be developed and more AI and sensor technologies will be promoted to track the quality [45, 48] and safety of produce (One Health Solution) [44]. In addition, alternative food sources such as protein from insects and algae will be offered as animal feed instead of plants [35, 57].

2.3 Methodologies in Literature

A 2012 study conducted in India modeled crop yield based on different climatic conditions and evaluated the model using R squared and RMSE [50]. A strength of their model was the inclusion of multiple parameters—such as dry matter yield, digestibility, and crude protein content, offering a holistic understanding of a crop's feed value. However, the study also has limitations. The trial was conducted in a single location and over one growing season, which may not fully capture the diversity in performance due to differing environmental or soil conditions. This fault was realized evidently in their figures. While they were able predict Indian feed crops until the year 2030, their graphs exhibit fluctuations in the years leading up to 2012, but on years following 2012 only display a smoothed line. The model thus failed to account for the natural variability in feed crop production. This is not the only study which has found fault in linear models for feed crop prediction. Another article, published in Journal of Applied Science and Technology Trends, found different accuracies for linear models based on the type of feed crop [51]. In addition, the article noted that although linear models take less time to produce an output, they have been shown to have less accuracy in predicting feed crops than polynomial models.

Researchers, T. Le Cotty and B. Dorin, calculated future feed crop requirements based on livestock population trends and feed conversion ratios (FCRs) for different animal types [34]. Their study included comprehensive data from multiple countries, including the United States, China, Brazil, and Europe. They used predefined scenarios to explore possible futures (such as increased feeding efficiency) instead of data-driven predictions from machine learning models. They synthesized the following formula: Total Feed Demand = (Number of animals $\times$ Productivity factor $\times$ FCR $\times$ Feed dry matter content). FCR stands for how much feed (in dry matter) is needed to produce 1 kg of animal product. Assuming developing countries adopt rich-country diets, but livestock are still raised using current feeding practices, there would be a 117 percent increase in demand for feed crops. If another scenario is realized instead, where there is a shift away from meat-based diets and improvements in FCR, there could be as little as an 8 percent increase in demand for feed crops. The primary downfall of their model is that, in reality, FCRs vary hugely by breed, system, climate, and feed quality.

An important point to consider when estimating the potential production of feed crops in the future is the impact of climate change. Tim Wheeler and Chris Reynolds utilized General Circulation Models. These are large-scale models used to simulate global climate change based on different greenhouse gas emission scenarios [55]. They found that corn was the feed crop most affected. This means countries that rely on these crops more heavily may need to adjust to other crops, such as soybeans. A fault of their model is that weather conditions vary greatly by region, and cannot be generalized to a worldwide perspective. A more accurate prediction can be produced from models specific to each country.

Scientists at the American University of the Middle East analyzed multiple machine learning models for feed crop prediction. They concluded that Random Forest consistently performed best across most crops and regions [13]. Gradient boosting multi-layer perceptron models also showed competitive performance, but were more complex to optimize due to sensitivity to outliers and the need to fine-tune hyper-parameters. K-nearest neighbors and Support Vector Regression were computationally slowest and did not generalize well to large-scale feed crop data. Previous research on food prices has shown linear regression to be a valuable tool to gain insight into the data. The researchers Headey, D. and Hirvonen, K, found that adding an error component to the linear regression improved results [24].

2.4 Project Plan

Our analysis begins with an extensive cleaning of the data in preparation for the figures. We begin with a simple statistical representation of the data. We began by plotting the variability of each feature, utilizing box plots. To clean outliers, we plan to adjust our year range and reorganize the price entries. Next, we seek to view the feed crop trends through time by a time-series graph. In addition, we seek to see these trends regionally as well. We perform the visualizations using Python in Jupyter Notebook as well as Tableau. To model feed crop pricing, we will use regression. To categorize which feature is most important to determine price, we will use binary tree forests. We also plan to integrate a model, such as LSTM, for time-series analysis.

3 Methods

3.1 Methods: LSTM Neural Network for predicting Commodity Type

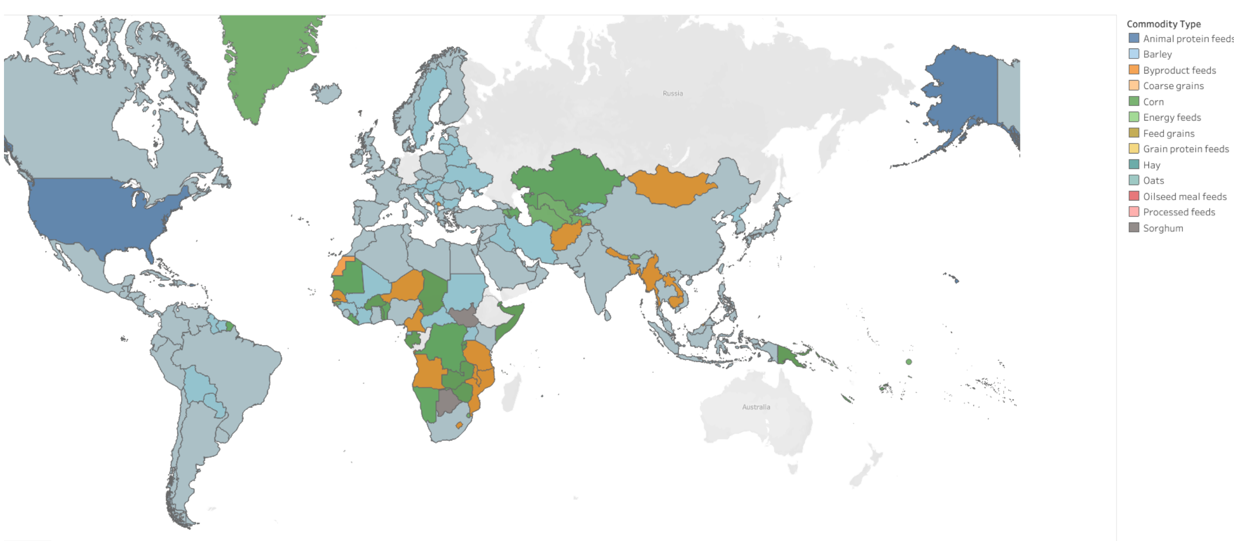

Figure 1: Most common commodity by country

Creating a commodity map in Tableau allowed us to see that commodity type varied by region.We thus decided to see if we could predict the commodity of a year in the future based on location. Continuing to examine our dataset, we performed PCA analysis focusing on commodity type with the goal of reducing dimensionality to make it simpler to identify patterns in the data.PC1, comprised primarily of Year and Location_ID, explains the most variance of the data. Corn, represented by green, has the most variance in the data, related to Price and Year, as seen by its large spread in the graph. This also displays that corn data dominates the dataset. The other commodity types show greater variance in the PC2, comprised mainly of yield, shown by their larger spread relative to the x-axis.

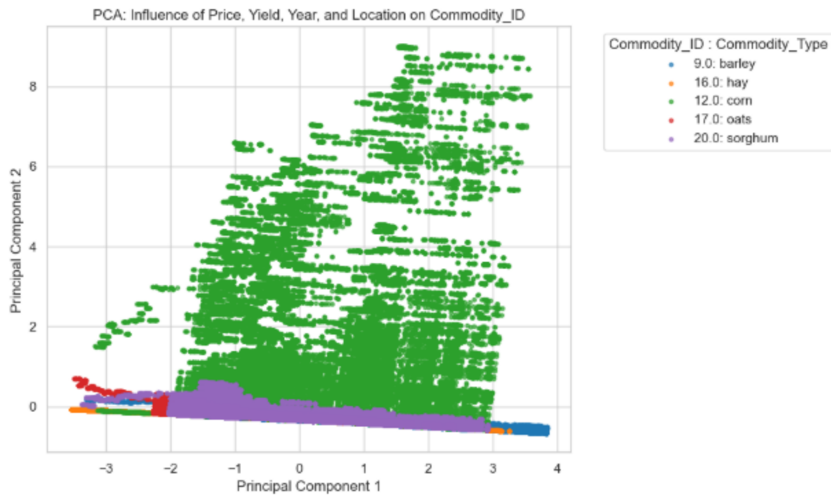

Figure 2: PCA analysis for commodity type

We continued our analysis by looking at the correlation matrix between the numerically represented features: Location_ID, Region_ID, Price, Year, and Commodity_ID. Out of these features, the ones that showed the greatest correlation were Location_ID, Year, and Commodity_ID. Determining the type of commodity that is likely to be the primary feed crop would be the most valuable to know out of these features. Determining the feed crop needed by a particular country in the future would allow governments to increase agriculture or imports to meet these predicted feed crop demands ahead of time. We selected to perform logistic regression for prediction purposes. Since Location_ID and Commodity_ID are categorical variables, label encoding will be the best fit for processing these. On the other hand, the Year is ordinal and continuous, so we utilized one-hot encoding to represent each year. Looking at the QQplot for the year data, it is clear that the data is not normally distributed.

In our project, to better fit a normally distributed dataset, we begin by performing a logarithmic transformation on the Year column. Also, by deleting years previous to 1955, the Year data now more closely follows the uniform distribution.

Finally, we are ready to perform a long-short-term memory neural network model to predict Commodity_ID based on Location_ID (country) and Year. The model has an R-squared score of 0.7052420244627626. This means that the machine learning model is able to account for about 70 percent of the variability in the Commodity_ID value.

3.2 Methods: Factors Most Affecting Price

We began this by analyzing the Price column of our dataset. The price column was entered in various measurement types such as dollars per bushel, cents per pound, etc. We began by converting all entries to dollars per 1000 metric ton. Since the data had to be scaled correctly, we converted all price units using standard conversions by the USDA [23].Wondering if price fluctuates by month, we visualized their relation.

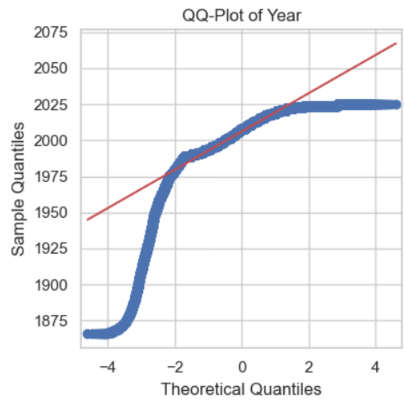

Figure 3: QQplot of Year

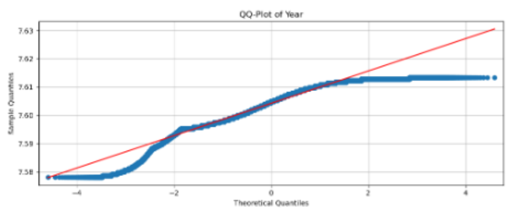

Figure 4: QQplot of Year data after alterations

Seeing that the bars did not differ significantly in height, we decided to explore other factors that could affect price. We chose to focus primarily on location, year and commodity type.

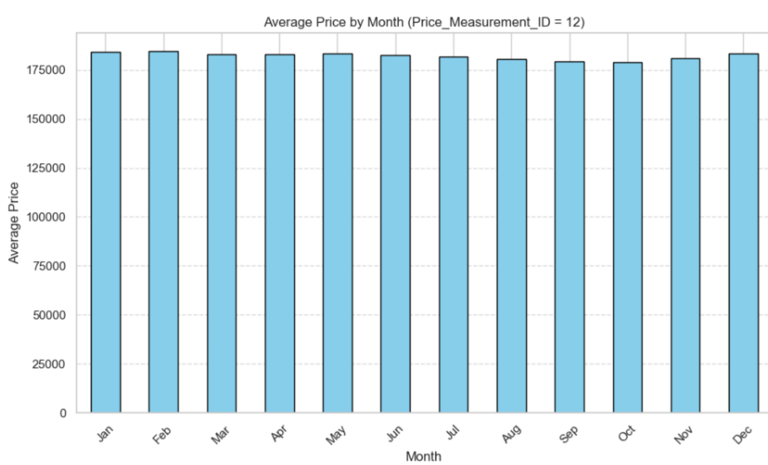

Figure 5: Prices in dollars per 1000 metric ton

We continued our analysis by plotting a correlation matrix. Unfortunately, it was unable to represent location or commodity type, since these were categorical variables. However, the correlation matrix was able to affirm that there was a strong positive correlation between Price and Year.

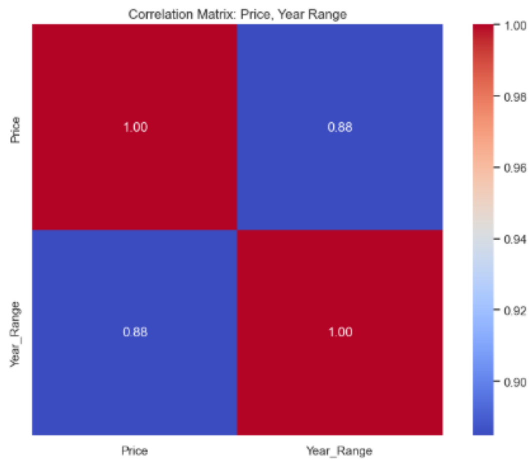

Figure 6: Correlation between Price and Year

Thus, to answer the second research question, we decided to use random forest to identify feature importance, and our main features that we assume influence the price fluctuation are location, year, and population. Researchers Hu, Liangyuan and Liu, Bian and Ji, Jiayi and Li have shown that using components of binary tree forests can be an effective way to predict feature importance for stroke [26]. Scientists at the American University of the Middle East analyzed multiple machine learning models for feed crop prediction. They concluded that Random Forest consistently performed best across most crops and regions [13]. The same can be applied to our model. After dropping rows containing null values, we then split the data into training and testing sets. Also, we calculated the root mean square error (RSME) and R-squared as 65887.40325307663 and 0.8613502992858455, respectively.

3.3 Methods: Feed crops trends specific to the United States

A great portion of our data pertained to the United States specifically, so logically we wanted to hone in our analysis on the regions of the United States. We began with filtering out unneeded data, converting all price types to dollars per 1000 metric tons, and checking to see if United States price data followed a uniform distribution. We utilized standard conversion remeasures [23]. In addition, we found that logarithmically transforming Price provided the best results to alter the data into a uniform distribution.

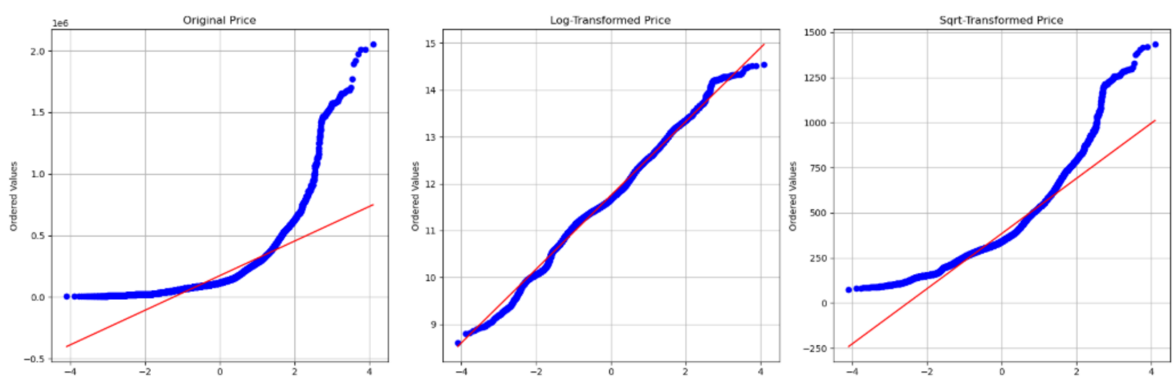

Figure 7: Logarithmic transformation of the price data provided optimal results.

Next, we utilized PCA analysis to identify which components affected Price the most. We chose to utilize PCA analysis because it has been shown by other literature to reduce dimensionality of the dataset [27].

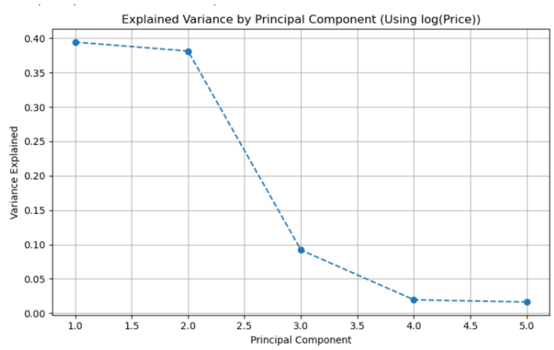

Figure 8: PCA Components 1, 2 and 3 account for most of the variability in Price data for the United States

The primary composition of PCA components 1, 2 comprised mainly of Year and Commodity_Type, and PCA component 3 comprised of specific locations in the United States. This means that in terms of determining price, year, and feed crop type are more important than the exact United States location. We then performed Ridge regression with polynomial components, optimized through GridSearch, to predict price in dollars per 1,000 metric tons. We then built a function that takes in commodity type, year, and location to give a price prediction. To make sure the function correctly displays price, not logarithmic price, we take the exponent of the preliminary result and display the resulting value.

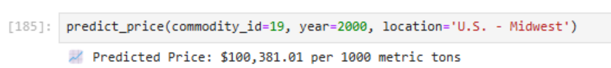

Figure 9: Example usage of price prediction function

4 Results

4.1 Results: Commodity Prediction

We sought to predict what the commodities would be in the future. By doing so, countries could predict what feed crops they would need to allocate resources or imports for. We attempted this first through a KNN regression, as it would be able to predict commodity as a categorical variable. However, since we wanted to use this to predict future commodities, we need to utilize a true time series model. By using an LSTM neural network, we were able to achieve an accuracy score of 89 percent. Using Keras Random Search Tuner, we selected the best model from ten models. In the future, we may choose to further fine-tune the LSTM model to better predict time series. Other data scientists have been able to replicate similar results by hyper-tuning parameters in their machine learning models [14]. Our model predicted that in the next 25 years, corn would become the most produced crop in all regions, and that Africa and Europe would be the top producers.

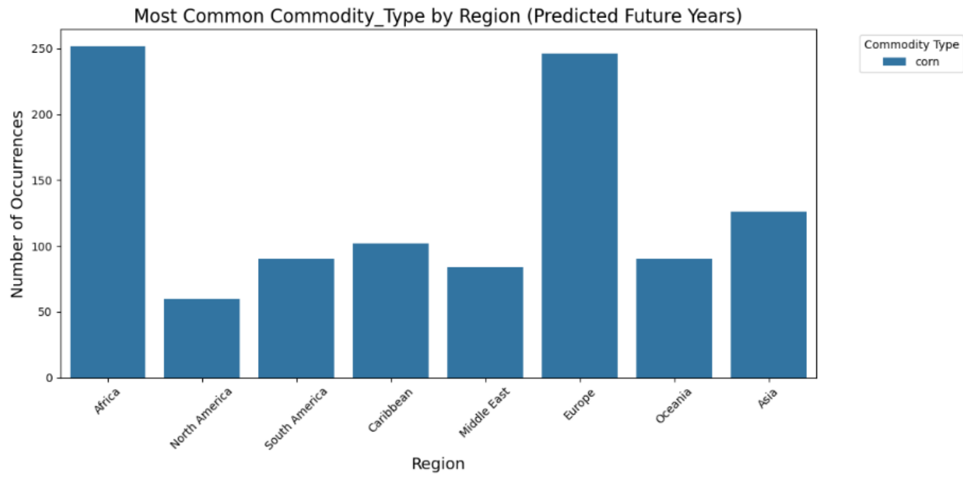

Figure 10: Average feed crop counts by region, 2025-2050

4.2 Results: Factors that influence price fluctuations

Following our decision to apply a random forest algorithm to determine which features influence price fluctuation, we noted that location, year, and commodity emerged as the three most significant factors, ranked accordingly. These findings suggest a relationship between feed grain prices and commodity types, differences in consumer location, and increasing time. The figure shows that location is the most influential factor in crop price, followed by commodity type and year.

Next, we plot the heatmap of random forest feature importance.The figure shows the percentage of each characteristic that directly affects the fluctuation of crop price as location 58%, year 33%, and commodity type 9%.

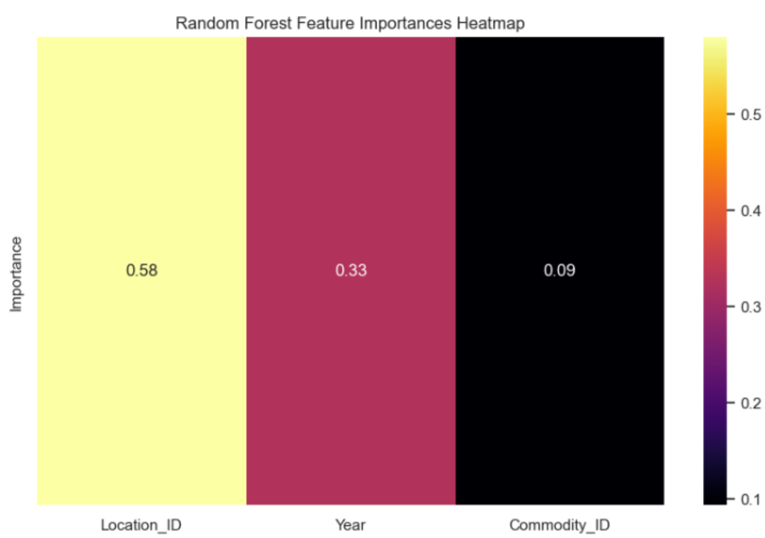

Figure 11: Random Forest Feature Importance heatmap

4.3 Results: United States Feed Crop Trends

We visualized the prediction for the top five most prevalent feed crops in the United States: barley, by-product feeds, corn, oats, and sorghum. Our model was able to show the overall trends. However, we need to look into whether the model is truly predicting price trends based on Commodity_ID and year or if it is merely showcasing inflation trends through the years. One issue with the model is that it cannot predict peaks and valleys, as we can see the smooth line after 2025 compared to the years prior to 2025. This is a common pitfall in regression models [1]. However, it still predicts the average prices accurately enough, with an R-squared value of 0.8094, for the United States to budget accordingly.

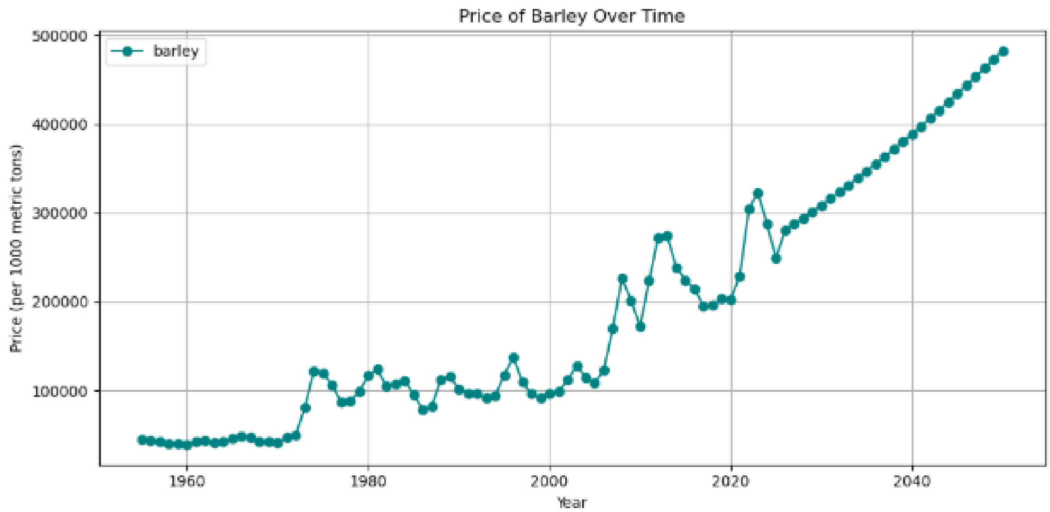

Figure 12: Corn feed prices in the United States 1955-2050

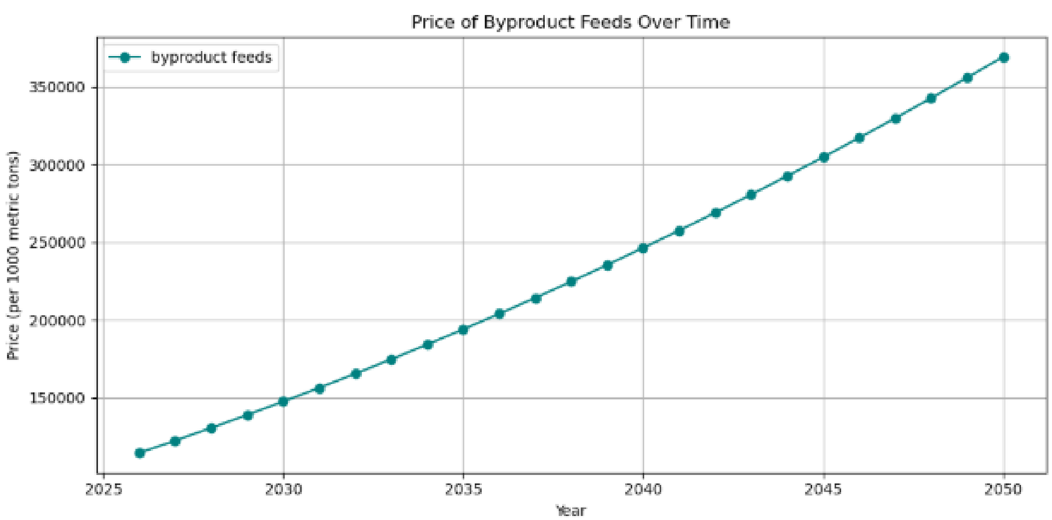

Figure 13: Byproduct feed prices in the United States 1955-2050

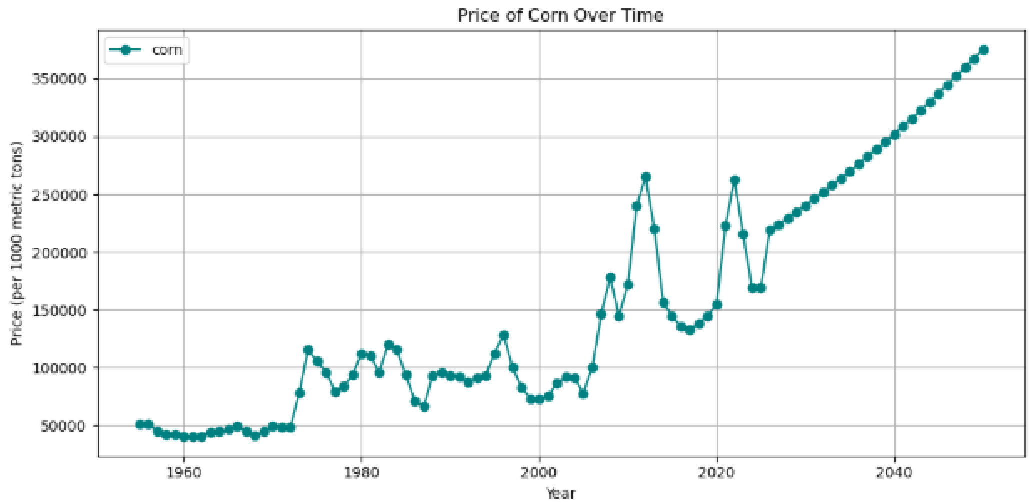

Figure 14: Corn prices in the United States 1955-2050

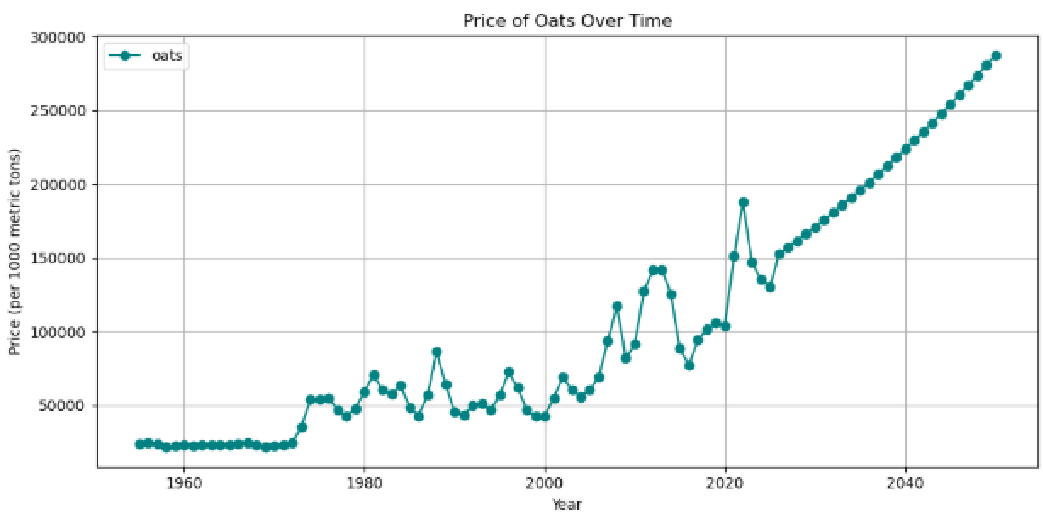

Figure 15: Oat prices in the United States 1955-2050

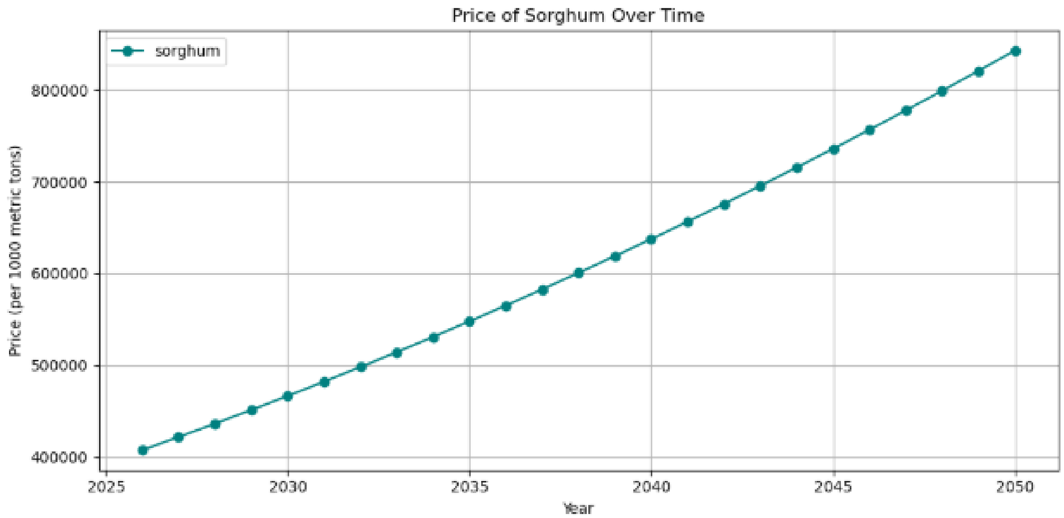

Figure 16: Sorghum prices in the United States 1955-2050

5 Discussion

5.1 Discussion: Recommendations

Based on the findings and methods explored in this study, we propose several recommendations to guide future research in feed grain analysis. For one, including real-time weather, soil, and satellite data would help account for local environmental variability, which was not represented in our model. Other researchers have utilized General Climate Circulation models to conclude that rainfall has a significant effect on corn yields in the southern United States [9]. This suggests that our lack of climate data is a major downfall of our model. Shown in our increased accuracy for our United States model, over our models including all countries, we recommend developing separate models per geographic region. Gathering data on more conventionally introduced feed types, such as those that are insect or algae-based, would aid in understanding future feed trends more dynamically. As industries are becoming increasingly climate conscious, insect or algae type feeds may outpace more traditional feeds, such as corn and soy [6]. In addition, future researchers should consider down-sampling the corn entries to improve the balance of our dataset for further applications.

5.2 Discussion: Challenges

Data cleaning was the most tedious part of our project. The most problematic part of our data was the Price column, which we found to have statistically great amounts of variability and outliers. One problem was that the Price column also contained information for yields. Since these are two different variables, we had to separate them into two distinct columns. Another issue with the price column was that the values had different measurements, for example some of the values were stored as dollar per ton while others were stored as cents per pound.

Our first research question is: "Can predictive modeling be used to determine future crops?" Our main goal in answering this question is to find a model that can predict the future trend of feed grains by year and location. However, after plotting a linear regression, the resulting plot appeared unusual, with the linear line not fitting the data well. Consequently, we decided to create a QQ-plot to assess the normality of the price and year features. This presented a challenge, as the data exhibited skewness and was not normally distributed. To address this, our team decided to apply a logarithm transformation to normalize the price feature distribution. One issue we encountered while using our LSTM model is that our model originally was predicting values such as 0, which is not a valid commodity type. We had to implement commodity mapping to fix this.

Another challenge we encountered was identifying the appropriate model for our third research question: "How does US feed grain consumption evolve over time?" Initially, we considered clustering; however, we determined it might not be the most suitable approach for predicting trends, particularly when considering the temporal aspect. Additionally, we implemented feature engineering techniques such as Principal Component Analysis (PCA) to reduce the dataset's dimensionality to identify the most significant features. We attempted to utilize the K-Nearest Neighbors (KNN) model, but it was unable to account for trends over time. As a result, it predicted a flat line for future prices, which is logically faulty. Therefore, we applied Ridge regression for prediction. The model's performance was evaluated using metrics such as Mean Squared Error (MSE) and R-squared (R2).

5.3 Discussion: Next steps

In the subsequent steps, after developing models to understand the relationships between price, year, and commodity, as well as identifying the most common commodities in the agricultural dataset and regional trends, we can apply these findings in future work. For example, we could enhance the precision of agricultural modeling by integrating our models with satellite and weather data. Furthermore, we can develop additional models to estimate the carbon footprint per feed type. Other researchers have found a strong correlation between feed crop prices and fuel demand as well as climate conditions [38]. Although we tried originally concatenating a dataset with the feed crop dataset, which contained GDP and CO2 information, the data could not be transformed to a uniform distribution. Looking for other datasets that may be able to be utilized, could bring insight into how these factors affect feed crop trends.

6 Conclusion

The global consumption behavior and production of grains has changed significantly over the past decades [7, 29, 39, 42, 46, 53], influenced by a number of factors, such as population growth, agricultural price volatility, post-World War II (1962-1994) consumption behavior changes, and technological advances during globalization [2, 8, 11, 21, 25, 35, 37, 44, 48, 54, 56]. These factors have both direct and indirect impacts on the structure of the grain industry in different regions of the world [4, 20, 36]. Consumption trends in each region vary depending on the factors and challenges faced by each region [22, 43, 57]. The analysis using machine learning, random forest, and time-series analysis will show the production and consumption trends in different regions and indicate the factors that affect grain production accordingly.

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Appendix A

Project code: https://github.com/abarletta99/DAT490_capstone