15

The application of artificial intelligence assurance in precision farming and agricultural economics

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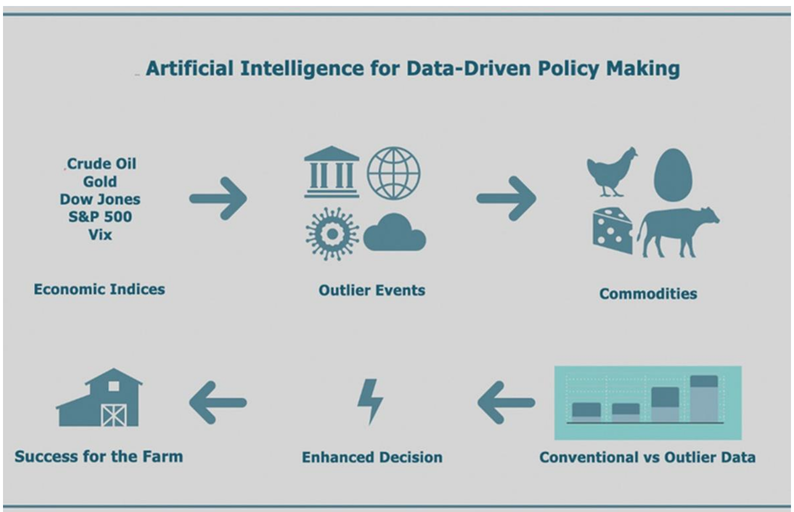
Graphical abstract



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Abstract

Agricultural policy has traditionally been conducted in an ad hoc manner, generally, by responding to natural disasters instinctively or managing unavoidable causes through the implementation of short term financial compensations or long-term loan and insurance programs at farms. The presented model, namely AI2Farm, provides farmers with predictions during conventional and unconventional times to compensate for the little to no guidance that policies, such as the Farm Bill, provide for spur-of-the-moment decisions needed to be made that arise from outlier events.

Farmers are an integral part of our economy due to their ability to manage market supply and demand expectations that solidify the nation's food security. Therefore it's important that farmers have access to the most up-to-date technology to make sound decisions that are in the best interest of rural and urban communities. Machine learning (ML) models measure associations, correlations, and causations of global and domestic events via commonplace financial indices with the production, consumption, and pricing of global agricultural commodities in the United States. Consequently, a deeper understanding of changes in behavior displayed by farmers as a result of outlier events aid in the ability to determine how precision agriculture can best assist farmers in the decision-making process. This entire set of information is lastly applied to the analysis of farms in the state of Virginia with smart tools and equipment that can benefit from models such as AI2Farm; the model and its results are presented and discussed.

Keywords

Outlier detection, economic indices, precision agriculture, smart farms

Highlights

- Artificial Intelligence (AI) systems are deployed to enable precision farming activities
- Data from economic indices such as the Chicago Board Options Exchange's CBOE Volatility Index (VIX), Gold, Oil, S&P 500, Dow Jones (DOWIA), as well as commodity data from the United States Department of Agriculture (USDA) are used
- Conventional and outlier-based predictions are presented as two alternative scenarios, where the farmer can choose from both scenarios depending on their current context
- Outlier events considered include: political, financial, environmental, health-related, global, and domestic events

- While most precision agriculture tools present localized recommendations that are disconnected from the world's state-of-affairs, the presented method provides a conventional recommendation, as well as one depending on events and their effect on farming

15.1 Introduction

The field of Precision Agriculture uses a variety of technologies, such as sensing, information technologies, and mechanical systems, to manage different parts of a field separately (USDA, 2018). The act of adopting such practice and applying it to day-to-day farm procedures is known as Precision Farming. Precision Farming provides some sense of stability amidst conditions such as weather and market demands that are natural actors within agriculture at the local and global level; protecting one's commodities and maximizing economic yield in the long run. Although farmers grow accustom to such conditions, there are instances where outlier events occur that overwhelm current monitoring and forecasting tools; prohibiting farmers from making sound decisions.

Formal acknowledgment of economic fluctuations are not merely enough to form an understanding as to *how* and *why* the extremities of outlier events vary and occur. What is required, rather, for precision agriculture, is the intersection of policy and economics to enable data scientists and public policymakers to make more informed decisions.

It is known that political events directly or indirectly affect the economy and VIX (Shaikh, 2019). COVID-19, which began at the end of 2019, is an outlier event resulting in vast disruption on the United States economy and financial markets; all of which was unforeseeable for many (Brown et al., 2021). The United States is a country that values individualism over collectivism; one where individuals are reluctant to participate in a cause if it's an inconvenience or burden to themselves despite the protection that it may provide to their neighbors (Vandello and Cohen, 1999). In turn, the notion of individualism further exacerbated the issue of COVID-19.

The manner in which the formal announcement of COVID-19 within the United States unfolded left little room for any current intelligent algorithm to be of use. Food insecurity became an immediate concern and reality for families across the nation. Consumer consumption increased as states were advised to go into lockdown, which strained retailers across the nation. The relationship between agriculture and this particular outlier event will be a reoccurring example throughout this chapter, because, for many, this obscure event is the most relevant and well known outlier in recent memory.

This research is concerned with the effects of an outlier event, such as the pandemic, on the commodities of animal products within the United States. The pandemic is multifaceted in the sense that it can be categorized as a global and political event, which had a direct impact on the production of goods. The distribution of vaccinations, a more recent development to offset the spread of the coronavirus, for example, had a direct relation to the health of farms. The Purdue food and agriculture vulnerability index estimates nationwide, "over 496,000 agriculture workers have tested positive for coronavirus, with over 3000 in New York State alone" (Purdue, 2020). The management of their fields and crop production was jeopardized alongside their health.

The Purdue food and agriculture vulnerability index in collaboration with Microsoft served as a baseline in terms of establishing the scholarly work that is already available, and identifying what can be improved upon. Purdue University "combined data on the number of Covid-19 cases in each U.S. county with the county's total population, the U.S. Department of Agriculture data on the number of farmers and hired farm workers in each county, data on agricultural production of each county, and lastly was able to estimate the share of agricultural production at risk" (Purdue, 2020). The visualization of loss of production within various states was useful in developing a deeper understanding of the struggles within the agriculture industry, more specifically during an outlier event. Though the loss of production impact for a given commodity is an aspect of agriculture research, it's unable to be useful for prediction of the other outlier events considered in this work as well as their relationship with economic indices. In this sense, we're able to distinguish this research from Purdue University and other existing scholarly work.

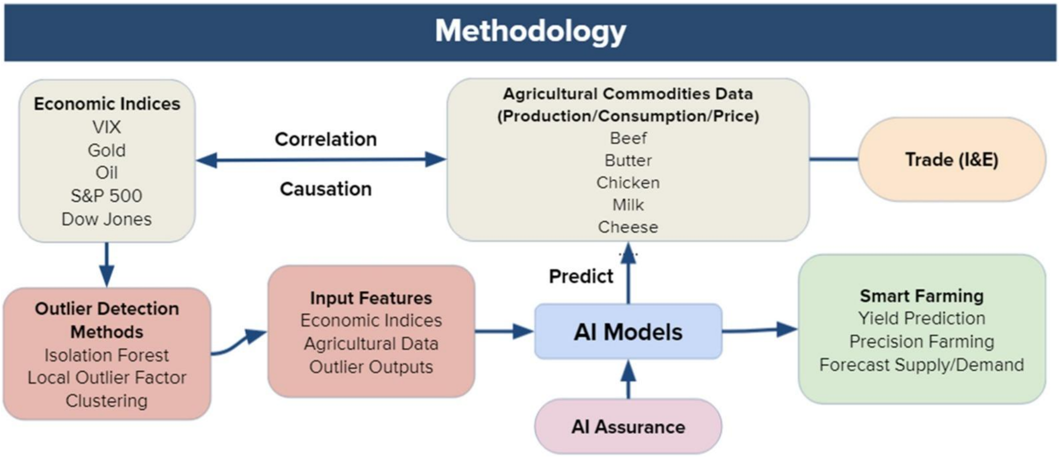


FIGURE 15.1 The AI2Farm method.

15.2 AI for smart farms

Beginning on the far right corner and continuing left in Fig. 15.1 of the AI2Farm model, the commodity of interest is observed alongside the six chosen economic indices to understand their relationship when fluctuation occurs. An outlier detection technique develops through the use of ML algorithms (i.e., isolation forest, autoencoder, K-means clustering, support vector machine) to detect unusual/outlier points on VIX, S&P500, gold, DOWIA, and crude oil indices. By properly labeling outlier data points, we're able to predict future outliers as well from the models. Definitions of outlier events for mentioned data are any anomalous dataset that behaves abnormally among the rest of the population, which in turn indicates particular events in the real world that cause the datasets to behave abnormally. Successful detection of outlier events deepens one's understanding of the effect of social/political impacts on smart farms. Both supervised and unsupervised learning models are used when comparing each of the model's performance matrices.

As it relates to the desire to centrally focus on AI for econ and international outlier events, for the purposes of technology and science policy, we're inclined to ask the following:

(a) *can policy scenarios be built to validate and optimize outcomes of different data-driven policies?*
(b) *can an economic causality model define the causes and effects of global outlier events using learning (from economic indices) and assured AI?*
(c) *can AI models factor outlier events into economic predictions to support farming decisions differently during outlier events vs. "conventional times"?*

The three questions above differentiate our research from current standing studies that merely focus on COVID-19 or another singular outlier event for that manner (Gruère and Brooks, 2021; Elleby et al., 2020). It is here we shift our focus towards weather; an outlier event that has been documented for centuries. Weather conditions, such as temperature, rain, humidity, moisture, and wind speed all impact yield production. Although documentation of such conditions through the USDA weather archives remain in use by farmers, rise in temperature caused by global warming will result in more persistent weather anomalies that will increase the need of better weather forecasting and question the use of traditional farming methods (D'Agostino and Schlenker, 2016). The urgency to implement a new form of predictive modeling pertains only to weather, just one outlier of many, all the while farmers are still subject to the impacts of supply and demand and market prices. This scenario illustrates that focusing on just one outlier event is not enough, because, in reality, farmers have to explore multiple avenues to make the best decision for their commodities. The aforementioned is why programs such as the USDA's Natural Resources Conservation Service and the National Water and Climate Center (NWCC), as traditional as it may be, might be losing their value (D'Agostino and Schlenker, 2016). Solely remaining responsible for producing and disseminating accurate and reliable forecasts and other climatic datum are trivial if it isn't specific towards a particular commodity or does not address other worldly events. Additionally, the manner in which they are collected and distributed to farmers is not of use. Generating forecasts in near real-time is the desired result of new and up incoming models, such as the AI2Farm model that is presented in this chapter.

The cost of production forecasts for US major field crops, for instance, is centered upon projecting net returns at the national level. The projected costs are based upon the previous year's production costs and projected changes in the coming year's indexes of prices paid for farm inputs (Knoema, 2021). Although the long-term baseline projections are in a sense reliable, they fail to provide an explanation as to why the fluctuation in prices occurred to begin with. The inclusion of economic indices is a starting point, but the lack of awareness surrounding outlier events and their impacts is lacking, and an area in which this research expounds. Conversely, research by the International Production Assessment Division (IPAD) of the USDA's Foreign Agricultural Service (FAS) does take outlier events into consideration. The primary mission of IPAD is to produce the most objective and accurate assessment of global agricultural production and the conditions affecting food security around the world (Becker-Reshef et al., 2010). Outcomes of the IPAD are monthly crop production estimates and early warnings of crop disasters. Though the outcome is similar in terms of early warning of crop disaster through the detection of weather outlier events, the method of collecting data is different in that it only focuses on one outlier event (weather) and doesn't concern economic indices. What continues to distinguish this research is that we have identified a new relationship that has not been studied before; considering the impact of both economic indices and outlier events. Observing one without the other is what separates research pertaining to localized versus global knowledge.

15.2.1 Correlation of economic indices and various commodities

The creation of the AI2Farm model begins with identifying the relationship between commodity production and the six economic indices. When evaluating economic indices and commodity data, it's imperative to understand the relationship between the two variables to determine whether or not correlation should be the basis of the decision-making process for a farmer. With the statistical knowledge that correlation does not equal causation, we run each causal and correlation value instead of one per production dataset. The process entails evaluating the highest causation, running the model, and then evaluating the highest correlation and running the model again to see which one has the strongest fit of the data. The Pearson's correlation coefficient is as follows:

$$r = \frac{\sum (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum (x_i - \overline{x})^2 \sum (y_i - \overline{y})^2}} \tag{15.1}$$

Pearson's correlation coefficient measures the following: if its p-value is less than the α setting (typically .05), we deem there to be a meaningful association, and the r value tells us whether the correlation is positive or negative.

As indicated in Fig. 15.2, the highest correlation goes to 1 and the lowest to 0; positive correlation is positive 1 at the highest point and the negative correlation is at -1 at the lowest point. For negative one as VIX goes up, beef will go down (exactly its opposite).

As indicated within Fig. 15.3, the x axis is the commodity, and the y axis are the indices. This is another form of representing how data are affecting one another. The correlation between the indices and the fluctuation of the commodities is indicated by either a strong positive linear correlation, as with cheese, or a nonlinear negative correlation as with beef.

15.2.2 Causation of economic indices and various commodities

Determining causality (a.k.a. causation), is the next logical sequence. In doing so, we hope to identify the causal score for the impact of each index on the production to inform farmers to use causation when possible, but when the strength is weak, to defer to correlation to determine which economic index they would like to focus on for each production.

DoWhy, an open-source Python library, is utilized to address the causal question in this research. DoWhy is unique in its ability to expand upon causal inference estimation methods, such as Python and R, that test statistical significance without the confirmation that the foundation in which it acted upon is in fact solid. Essentially, DoWhy minimizes the expectation of an analyst to not only provide their own causal model and checks for assumptions, but to provide it correctly in a manner fit for causal inference.

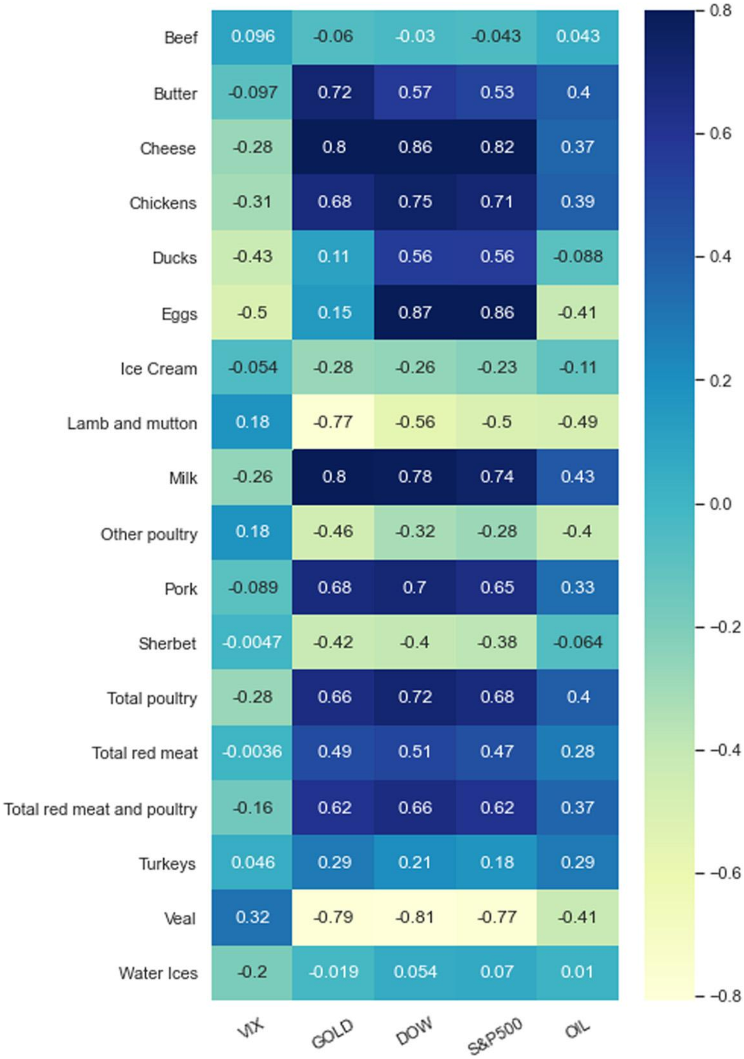
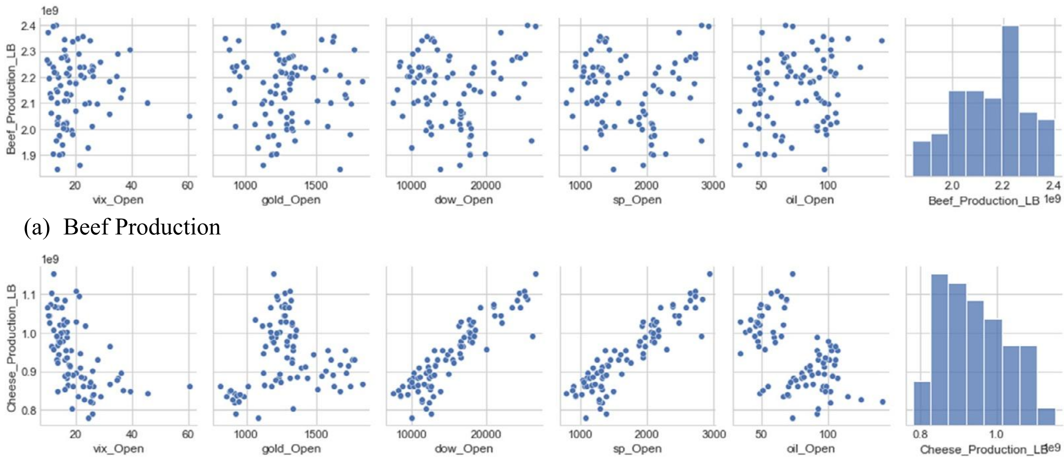


FIGURE 15.2 Correlation model between economic indices and commodities.

To relieve this burden, and to ensure that the steps prior to the estimation step were done correctly, DoWhy added an additional three steps to their pipeline, as shown in Fig. 15.4.

The four-step analysis pipeline includes the following: model, identify, estimate, and refute. Model causal mechanisms, identify the target estimated, estimate causal effect, and refute the estimate. This end-to-end li-



(a) Beef Production

(b) Cheese Production

FIGURE 15.3 Commodity Production pair plot for (a) beef and (b) cheese.

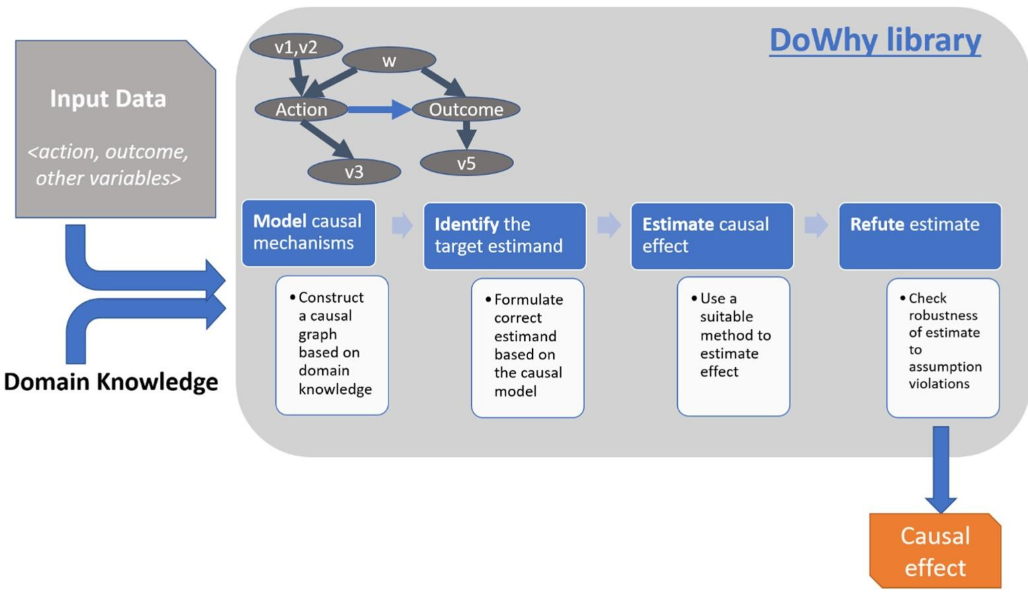


FIGURE 15.4 The four-step analysis pipeline in DoWhy (Sharma and Kiciman, 2020).

brary for causal inference provided the certainty necessary to estimate the causal effect.

Table 15.1 includes the results gathered using DoWhy. Shown above are five columns of the commodities and economic indices and eighteen rows

Table 15.1 Scores processed by DoWhy for causation between each commodity and economic indicators.

	Crude Oil Open	Gold Open	DOWIA Open	S&P500 Open	VIX Open
Beef	0.226021	−0.23521	1.608905	−1.42056	0.28295
Butter	−0.01532	0.477177	0.154803	0.145163	0.090398
Cheese	−0.05527	0.406332	0.239261	0.367241	0.110741
Chickens	0.10447	0.165347	0.305438	0.169931	0.044098
Ducks	−0.02345	−0.15335	−0.53592	1.017804	−0.21246
Eggs	−0.04621	0.043418	0.544103	0.186939	0.020712
Ice cream	0.02511	−0.12444	0.209716	−0.46338	−0.24881
Lamb and mutton	−0.0291	−0.45765	0.293928	−0.43749	0.064549
Milk	0.017964	0.4296	0.0652	0.43674	0.0775
Other poultry	−0.20287	−0.14632	−0.16872	0.058221	0.179605
Pork	0.015955	0.235899	0.84366	−0.28956	0.275482
Sherbet	0.271992	−0.40333	0.401844	−0.60832	−0.20088
Total poultry	0.121128	0.140361	0.444497	0.037026	0.079839
Total red meat and poultry	0.120495	0.089676	0.892369	−0.41871	0.192183
Total red meat	0.119753	0.030156	1.418313	−0.95388	0.32411
Turkeys	0.28781	−0.06445	0.502205	−0.25064	0.291053
Veal	0.024031	−0.47032	0.558691	−1.09531	0.070137
Water ices	0.037014	−0.04263	0.23056	−0.189	−0.2337

of the production datasets (crop/animal data). Linear regression is a statistical process to model the relationship between two variable; a method used within the third step of the pipeline to estimate the causal effect. Through the use of linear regression, DoWhy isolates one independent variable from the other independent variables to observe the effect of one thing, whilst ignoring the effects of others.

In the causal model, the arrows are reflective of indices and their "associated" production. The thought process behind using causation is to isolate one index and its effect on individual commodities: in this instance, beef. With the awareness that all five indices may have an effect on the commodity of choice, isolating all of the independent variables that we do not have control of results in more control groups. The result is a better understanding of which economic index is best to focus on for measuring production, and therefore helping with decisions on the farm. The data normalization formula used is as follows (Loukas, 2021):

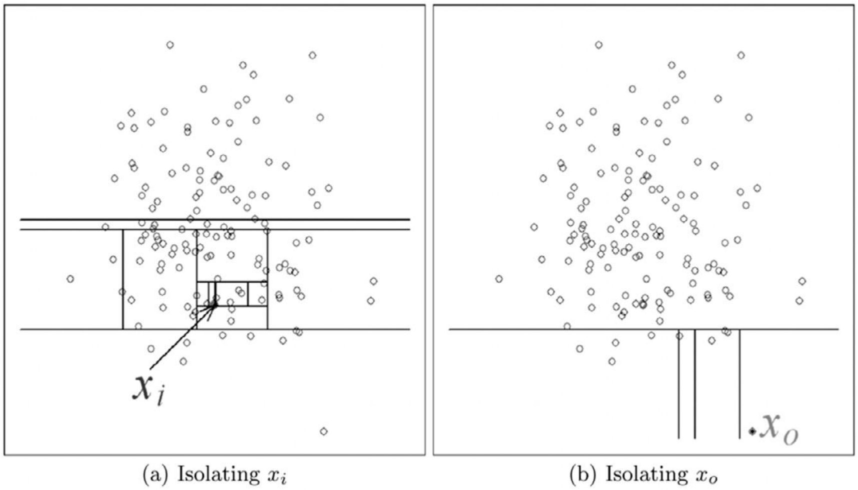
$$X\ scaled = x - \frac{xmin}{xmax} - xmin \tag{15.2}$$

The min-max scaler is used to normalize all stock price data in the range of 0 to 1 for each stock. Without this structure, it's a comparison between a large and complex index to a smaller index, which results in data bias issues further down the line.

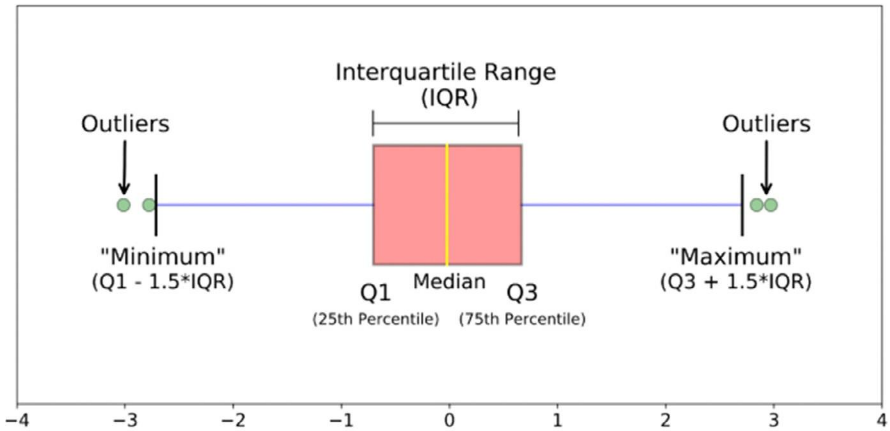
15.2.3 Scoring outlier events for the model and finding anomalies

The AI application begins with the introduction of outlier events; one from a generated algorithm and another from real world events. Both are chosen to ensure that the identification of outlier events isn't limited to the scope of the generated data, rather it is to the scope of that data and beyond with the real world events (a comprehensive list is manually collected). The unsupervised algorithm of choice is isolation forest or iForest to detect abnormal behavior within the economic dataset. This model-based method is the preference over existing distance- and density-based methods due to its ability to handle larger datasets and identify anomalies at a quicker rate. The concept of an isolation forest is as follows (Liu et al., 2012) (see Fig. 15.5):

> *"In a data induced random tree, partitioning of instances are repeated recursively until all instances are isolated. This random partitioning produces noticeable shorter paths for anomalies since (a) fewer instances of anomalies result in a smaller number of partitions-shorter paths in a tree structure, and (b) instances with distinguishable attribute-values are more likely to be separated in early partitioning. Hence, when a forest of random trees are collectively producing shorter path lengths for some particular points, then they are highly likely to be anomalies".*



(a)



(b)

FIGURE 15.5 Statistical method: (a) 2D dataset of normally distributed points where X_o is an outlier point (Liu et al., 2012) and (b) interquartile rang (IQR) (Galarnyk, 2020).

Model design: *Sklearn* is used for model design; in addition to the isolation forest algorithm. Both libraries enable the research to encompass the contamination rate; the percentage of an outlier that can be approximately guessed out of total data points. The contaminate rate is determined through the use of the IQR, or interquartile range, as a measure of how widely varying a univariate dataset is. It's the distance between the .25-

quantile and the .75-quantile; also known as "upper" and "lower" quartiles. We consider the middle data segment as normal data points, whereas beyond this range lies outlier points. The IQR method is used on preprocessed economic data (crude oil, DOWIA, S&P 500, gold, and VIX) to collect the contamination rate both in the daily and monthly economic index dataset.

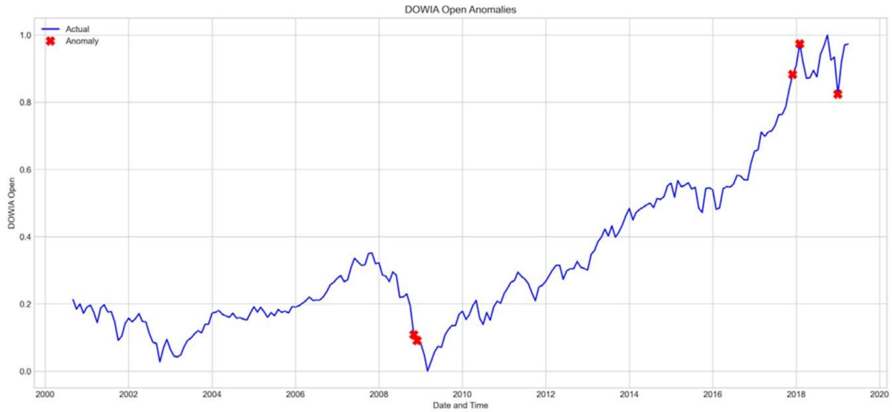
Following the collection of scores and anomalies, red anomalistic points are displayed from the generated isolation forest algorithm. Red anomalistic points are represented by an "x" in Fig. 15.6. The model performance is further tested to reveal a >90% accuracy in terms of labeling the points as the model is supposed to isolate the outliers. See Figs. 15.6 and 15.7.

The graph indicates the anomaly data point distribution from economic indices and major global events with regard to trade/international affairs. Determining the distribution is the act of putting all of the values in a straight line and being able to determine which value has the most density. For instance, the value for VIX open is (0.1), which is approximately the median of the distribution. With one peak, VIX open would be considered univariate, while Gold Open, which contains two peaks instead of one, is multivariate.

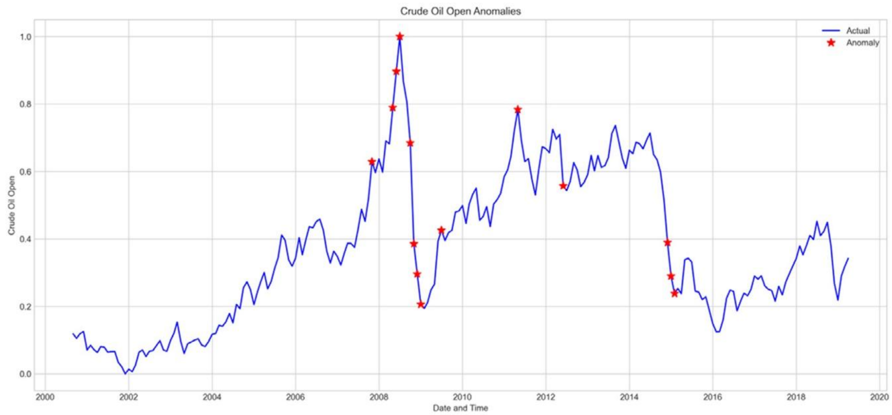
15.2.4 Outlier classification and labeling

Interpreting the red anomalistic points at face value would lead one to believe that those points are the only outlier events within that given year. That observation would be mistaken since the red anomalistic points are only reflective of outliers within that dataset. The purpose of the generated algorithm is to have accuracy in labeling the points as an outlier event, which it accomplished. Ensuring that the outlier events that could not be reflected within the dataset are being captured is the next logical step in this process. To accomplish this, we classify different timeframes as outliers and non-outliers separate from the generated model.

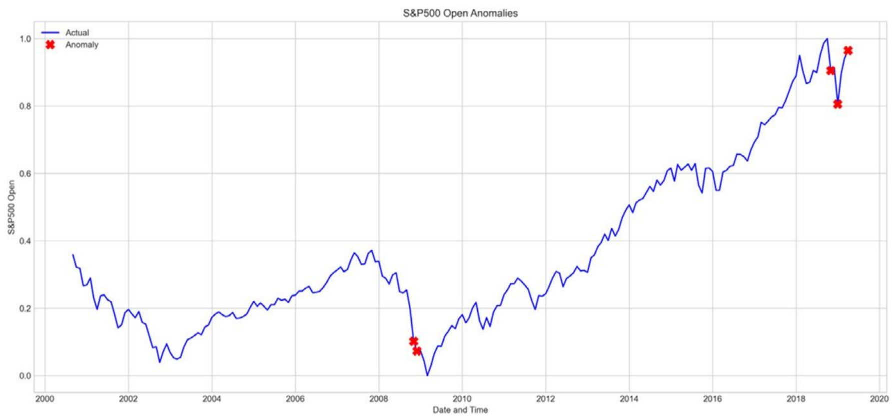
Fig. 15.8 is an illustration of labeled outlier events collected outside of the generated model during the year of 2001. The identification of the outlier events within the figure is not swayed by the time frame per se that the red anomalistic points provide (high peaks and clusters in one area). Rather, the entire year is looked at holistically and all months are considered regard-



(a) DOWIA Open Anomalies

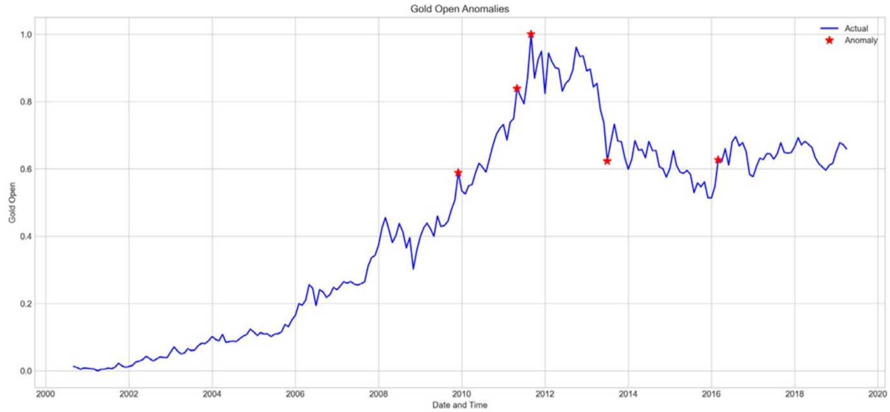


(b) Crude Oil Open Anomalies

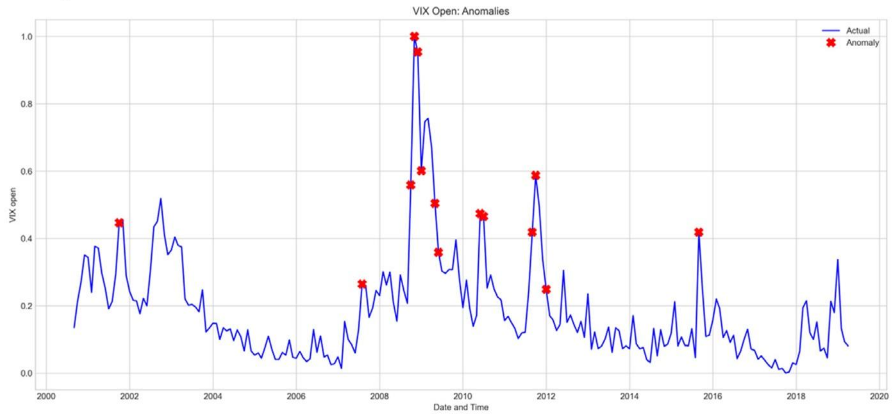


(c) S&P500 Open Anomalies

FIGURE 15.6 Anomalistic data points: (a) DOWIA, (b) crude oil, (c) S&P500, (d) gold, (e) VIX.



(d) Gold Open Anomalies



(e) VIX Open Anomalies

FIGURE 15.6 continued

less if there is a peak of high activity indicated in the generated algorithm beforehand. For instance, the early 2000s recession and 911 attacks are consistent with the generated algorithm, but the trade status shift with China is certainly one that did not fall within the algorithm. The process of going through each year once more to ensure that all possible outlier events are accounted for is repeated for each year.

Afterwards, the outlier events are filtered and classified into one of the following categorization ID's (Financial=1, Global=2, Pandemic=3, Political =4, Weather=5). The act of classifying an outlier event broadens the narrow scope of weather that agriculture is accustomed to. When this infor-

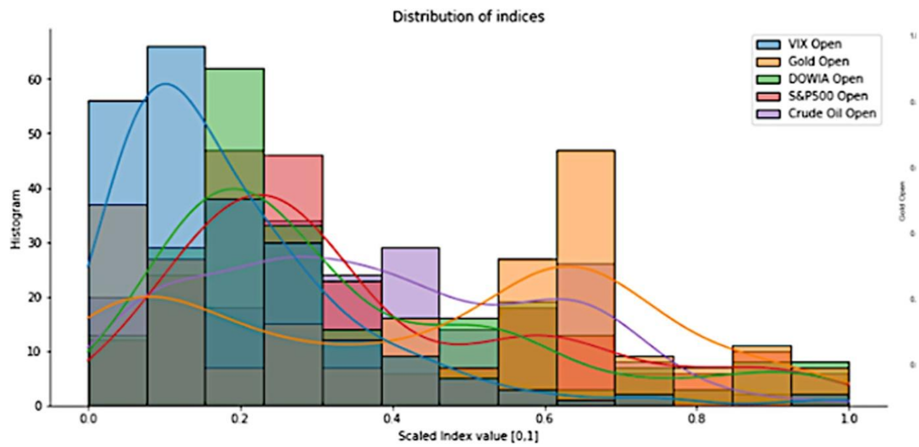


FIGURE 15.7 Distribution of indices.

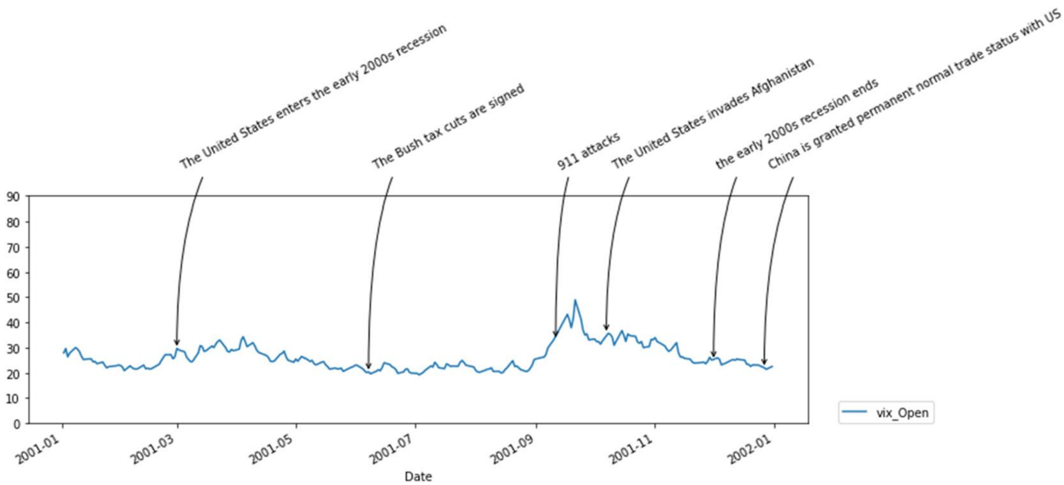


FIGURE 15.8 Labeled outlier events.

mation coincides with fluctuation input from economic indices, it places farmers in a better position to make better decisions. In that sense, the AI2Farm model appeals to the liking of Verdouw et al. (2015) who depicted the following management functions:

1) analysis and decision-making: comparing measurements with the norms that specify the desired performance (system objectives concerning e.g., quantity, quality, and lead time aspects), signaling deviations, and deciding on the appropriate intervention to remove the signaled disturbances.

2) intervention: planning and implementing the chosen intervention to correct the farm processes' performance.

15.3 Insight into data driven farming

The intent of each site visit is to develop a better understanding of factors that are a hindrance to yield production and efficiency on farms across the Virginia Tech network as a whole. Variance in opinion occurred due to each farm specializing in a different aspect of agriculture from one another. Kentland Farm focused on (crops, breeding, plants), McCormick Farm focused on (cattle, feed, Animal Science), and the dairy complex focused on (Dairy Science). While in attendance, we observe what technology is already in use as well as what technology could be put in place to improve upon the current conditions. We then generalize responses as qualitative data to complement the preexisting categorization ID's (Financial=1, Global=2, Pandemic=3, Political =4, Weather=5).

For instance, a small grain breeder at Virginia Tech shared an example of a severe weather event example during the visit. In Virginia, wheat and barley are planted in the fall, go dormant over the winter, and come back in the spring to produce grain. When maturity happens, weather has an effect on whether or not it can be pulled out of the field in time or if they have the quality that's necessary to be a viable crop. Once grains are mature, barley specifically, the grain dries down and becomes ready to become a seed, carrying a certain level of dormancy with it. However, if they are rained on within the field, then they'll rehydrate and sprout within the field, while they're still in the grain head, which reduces the quality of the product. This severe weather event example added validity to the need of supporting smart farm initiatives to integrate new technologies into farming practices.

15.3.1 Kentland and dairy farm

Crop Management through the use of AI is actively being used at Kentland Farm. The method of crop management entailed; pre-mapping of land and crops, drone calibration, and navigation using GPS (Global Positioning Sys-

FIGURE 15.9 Prepared farm via vertical and horizontal lines for drone calibration.

tem). The quality of soil is ever so important for managing crop yields (Ge et al., 2011). To have an accurate depiction of the quality of the soil within the field, the farm is separated into equal boxes. Vertical and horizontal lines are then constructed for drones to be able to detect areas within the farm to know where the end and the beginning is and to provide data in that specific area. The farm is then prepared for the drone to fly above it and be able to take images and read every piece of land separately.

Figs. 15.9–15.13 are sample images from Smart Farms at Virginia Tech.

15.3.2 Shenandoah Valley Agricultural Research and Extension Center (SVAREC)

The Shenandoah Valley Agricultural Research and Extension Center (SVAREC) conducts pasture system research and beef cattle production within the confines of over 900 acres of owned and leased land. Cattle are used for breeding and various projects based upon (artificial insemination, weight, body condition scores, hip height, pregnancy checks, sex of the fetus, weight of the calf, etc.).

FIGURE 15.10 Wide-angle view of weather stations at SVAREC.

(a) SmartScale (b) Mechanical Feeder

FIGURE 15.11 (a) SmartScale and (b) mechanical feeder at McCormick farms.

Pandemic → **Global** → **Financial** → **Political**

FIGURE 15.12 Interconnected outlier event.

The large overlay of the farm includes the weather station at the top right corner as its focal point. Weather stations are a common piece of technology on farms used primarily for measurements of precipitation, air

(a) DeLaval Machines

(b) Afimilk Device

FIGURE 15.13 Dairy machinery installed at the farm: (a) DeLaval and (b) Afimilk.

temperature, dew point temperature, wind speed & direction, barometric pressure, soil temperature & moisture, and solar radiation. Additionally, virtual fencing accompanies this large area of land. Virtual Fencing "contains cattle by providing audio and electrical signals via a neckband device and assists in measuring activity, health variables, weight, location, movement towards water, and feed management. Animals are restricted in a specified area via receiving stimulatory cues, rather than through the presence of a physical fence enabling remote animal monitoring and movement control" (Keshavarzi et al., 2020). Enhanced mobility of cattle is an area in which farmers at Kentland are keen to continue to expand upon, which will be a part of future research.

Cattle control, having agency over cattle to produce a desired outcome or act in a desirable manner, is currently functioning as intended due to the following two technologies in place. The mechanical feeder is in use outside of the traditional sense during the pandemic to slow feed for slower slaughtering dips in consumption or national demand (top left) and the SmartScale is used for weight management. Data collected from such measures include the following: body condition, hip height, age, calving dates, hay amounts, feed costs, and weather data. All of which is part of economic analysis for public policy toward the Farm Bill (USDA, 2021). The definition of SmartScale and virtual fencing is as follows (Producer Smart Scale, year):

> *"SmartScale is a wireless scale system that captures animal weight, performance, and behavior each time it drinks water. SmartScale is a cloud*

> *connected, automated scale unit that utilizes existing pen water supplies to provide daily weight and performance for each animal in your pen. Customizable to fit most existing pen water supplies and integrates with SmartFeed bunks to provide high-quality, real-time data".*

Supply chain bottleneck is an example once more of how there's an overlapping of outlier events. Supply chain bottleneck is defined as congestion in the production system due to an increase in demand with limited capacity. The result, in this case, is supply overstock of cattle at a weight prepared for slaughter at a state too early. Supply chain bottleneck occurred when some meat processing plants shut down, preventing animals awaiting slaughter from being processed. Cattle producers had a "12.3% decrease in the price they receive. Although producer and consumer prices tend to move in unison, the supply-chain bottleneck caused by Covid-19 has likely caused a divergence" (Beckman and Countryman, 2021). Hence, why there was and still is a need for the feed management tool.

With this scenario, one will find that outlier events are overlapping in four out of the five categories. The pandemic impacted the world, which in turn negatively impacted the market, which in turn negatively impacted the farmers in such a way that involvement of the US Department of Justice (DOJ) was needed.

Although the DOJ has reportedly contacted the four big meatpackers (Tyson Foods, JBS SA, Cargill, and National Beef) to seek information related to an investigation into possible antitrust violations, concerns of price fixing during the pandemic will continue to mount (Johnston, 2020). As long as there is an imbalance and presence of middlemen in between farmers and consumers, profits will never make it down to small farmers, resulting in farmers across the country continuing to not get their fair share. The notion of living amidst a "broken market" due to anti-competitive practices and market manipulation by the meat packing industry rings true. This multifaceted outlier event will continue to impact farmers and constrain farmers to use technology such as the food monitor to alleviate the supply chain bottleneck when in fact the financial aspect of the diagram above is the root cause of the problem.

Now, that's not to say that there aren't outlier events that stand on their own. The identification of such events, especially outside of the typical weather outlier event, is equally as important. The ability to understand outlier events and to view them in this manner will aid in the decision-making process for farmers during both conventional and unconventional times. Thus making the AI2Farm model even more justifiable for its use in the future.

15.3.3 Dairy complex at Virginia Tech's SmartFarms

The dairy complex processes 2k gallons of milk every two days through automated milking. The data collected includes herd analysis, daily data for production, cow's health, activity tracking, milk quality, and infections. DeLaval machinery analyzes milk samples from lactating dairy cattle through somatic cell count (SCC) to monitor udder health and diagnose subclinical intramammary infection (IMI) in dairy cattle (Kandeel et al., 2017). The AfiMilk system is versatile and can be of use for their ICAR milk meter, integrated farm management SW, heat detection system, and milk analyzer (Berger and Hovav, 2013).

The overall consensus is that the newer technology is solely being utilized on the smart farms due to its function as a test bed for the development and testing of technologies; in other words, it's slower to be adopted by beef cattle producers outside of the Virginia Tech network. The hesitancy displayed by other farmers is due to a lack of trust. Trust in precision agriculture is dependent on recommendations that are "reliable, accurate, transparent, and fair than previous systems" (Gardezi and Stock, 2021). Essentially, requesting farmers to place trust in an algorithm or model which they are not familiar with and goes against traditional modes of farming that have been established over the years is bold from the researcher's standpoint. Farmers are no longer the sole reserve of experience, as cognition and decisions have increasingly become distributed between farmers and intelligent technologies.

15.4 Larger policy implications

Public policy is a course of government action or inaction taken in response to social problems. When written down as laws and directives, it serves as precedent in future cases to see whether or not the policy was being upheld or not. The government is a collective since it is not a unilateral decision-making entity (made by one person) and, under a democratic form of government, is *consensual* since citizens can elect who has the privilege of making decisions on their behalf.

The process of public policy begins with agenda setting (prioritization); how issues get defined as political and worthy of government attention or action by elected officials. Next is policy formulation, when a piece of legislation can be introduced as a bill by a certain congressman, through signature of an executive order by the president, or by bureaucratic entities. Following this step is policy implementation, the time lapse effects of such policy being in place. Lastly, policy evaluation uses data to see if the policy is working as intended.

In the political sphere, efforts to address agricultural issues have been made in an overarching manner. In *The fault lines of farm policy*, Coppess (2018) contended that farm risk is made up of two fundamental matters: market risks (whether lost export demand or oversupplied markets. These risks return prices too low to cover cost and profit needs) and weather risks (the dilemma between good weather that can result in massive crops that outstrip demand and lower prices and bad weather that can cause damage to crops that leave too little to cover costs and needs) (Coppess, 2018). Individuals and organizations who advocate on behalf of these concerns include the Secretary of Agriculture, the USDA, agriculture committees within Congress, farm lobbyists, and others. Concerns may be vocalized as a means in which to combat activities perceived as detrimental or an endangerment to society, to protect certain populations and or groups within society, or to promote certain activities that are deemed important.

Such concerns are expressed over the years and culminate into what is known as the *Farm Bill*. United States agricultural policy generally follows a 5-year legislative cycle producing a *Farm Bill* with the Agricultural Improvement Act of 2018 (Congressional Research Service, 2019) being the most

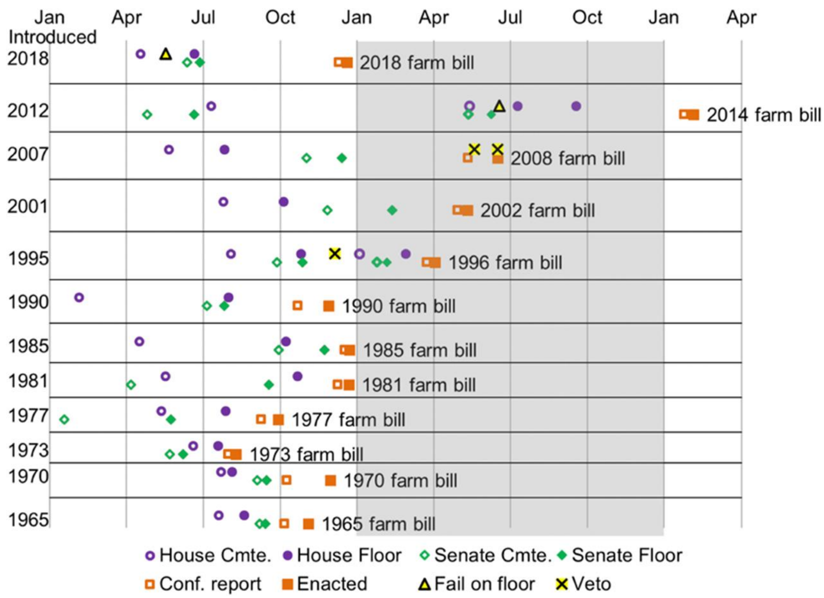


FIGURE 15.14 Major legislative actions on farm bills, 2018–1965 (Congressional Research Service, 2018b).

recent. Historically, there has been a trend of enactment occurring well after the original expiration dates. The possible consequences of expiration include "minimal disruption (if the program is able to be continued via appropriations), ceasing new activity (if its authorization to use mandatory funding expires), or reverting to permanent laws enacted decades ago (for the farm commodity programs)" (Congressional Research Service, 2018a). What's more, is that Farm Bill reauthorization has become more complex with the process of enacting a new farm bill varying from previous years as follows (Congressional Research Service, 2018b) (see Fig. 15.14):

> *"Prior to the expiration of the existing law has become more difficult. As stakeholders in the farm bill have become more diverse, more people are affected by the legislative uncertainty around this process. This lack of certainty may translate into questions about the availability of future program benefits, some of which may affect agricultural production decisions or market uncertainty for agricultural commodities."*

In regard to outlier events, the Farm Bill contains support programs for agricultural disaster assistance, such as Price loss coverage (PLC), Agriculture risk coverage (ARC), and the Marketing assistance loan (MAL) program. However, federal assistance to recover financially from natural disasters is a method that occurs after the fact and is not a preventative measure desired by most farmers. Responding in the manner of federal assistance qualifies as a short-run policy (primarily in the coming weeks) over which the "supply of goods and services can be altered into a better state for essential goods and services" (The Brookings Institution and Snower, 2020).

Specific efforts to accommodate farmers' needs during the pandemic included funding such as the American rescue plan, the U.S. Department of Agriculture's implementation of the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020, and much more (USDA, 2021). The pandemic was chosen in large part due to its illustration of how intricate and interconnected the market is. The global ramifications of the spread of the coronavirus were evident when policy adjustments were made simultaneously across the globe; adversely disrupting market and trade. An analysis of the distribution of measures undertaken by 54 countries during the first four months of 2020 provides some early insights into the emphasis, scope, and regional diversity of policy responses. The study found that temporary measures taken by existing countries within the international relations community, had "adverse effects on consumers (import restrictions or local promotion measures), producers (export restrictions), food chain actors (market distorting measures), and the environment (regulatory relaxations, input subsidies)" (Gruère and Brooks, 2021). In turn, temporary relief measures as a response to outlier events, is a double edge sword. Lifting measures at the conclusion of such an event not only will send the market into shock once more, but complicate the relationship of actors in the future.

Presenting information from the AI2Farm model to policymakers (U.S. government) would alleviate the need to disperse funding affecting the national budget on such short notice and lessen the reliance upon loans for commodities by farmers. Additionally, the data on outlier events could be used as evidence within cases such as the disparity between packers' profits and beef prices which have widened during the pandemic being brought before the DOJ, quickening the process for policy changes that would most likely occur before the typical 5-year legislative process.

The Farm Bill is faced with the daunting task of not only improving upon the bill from previous years, but also navigating uncertainty with the implementation of new procedures in the future. Despite the best effort of a well written bill, the inevitable zone of uncertainty diminishes the impact of such policies (Novak et al., 2015). Therefore successful production season would be simply unattainable if farmers weren't afforded the flexibility provided by the AI2Farm model and had to rely heavily on the details stated within the Farm Bill.

15.5 Conclusion

In this work, we posed the following question that is inverse of the typical way that agriculture farming is discussed: One should ask not what is the most efficient way to provide aid to farmers in the form of compensation for commodity and income losses following an outlier event, but rather what is the most efficient way to inform farmers about conventional and unconventional time to alleviate shock to commodity production. The AI2Farm model provides farmers with the much needed flexibility to persist within the ever changing environment within society.

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