Crop Yield Predictor for Small Farms in Monroe County, NY

by

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Contents

1. Abstract

There has been an economic shift recently towards larger farms, although small farms make up 91% of farms in the United States and are “more productive per unit of land than large farms” (Reynolds). One way we could help small farms compete and cope with climate change is through predictive analytics applications. However, these apps are catered more towards larger farms regarding prices and ease of use. If these tools were to focus more on the needs of small farms, they could help them make informed decisions based on predicted future yields. This is the goal of Yield Predictor, an application I developed that predicts the total yields for a specific crop users enter into the app. They will be able to see a scatter plot of predicted yields for the next 10 years based on two climate scenarios: RCP 4.5 (intermediate climate scenario) and RCP 8.5 (worst-case climate scenario).

2. Literature Review on Small, Family-Owned Farms

2.1 Local Case Study: Chase Farms

Before development, I conducted a literature review of small vs. large farms, neural networks, and current web artificial intelligence tools. Throughout this review, small farms will be defined as any intermediate family farm “whose operators report farming as their major occupation”, that earns between $100,000 and $249,000, and focuses more on growing crop products and not on livestock (20). A local case study that fits this description is Chase Farms in Monroe County, NY. They are a family owned farm that grows “fruit and vegetables along with soybeans, field corn and wheat” (Chase, 3). A typical year for the farm goes as follows: in late November and early December hand weeding is done in all fields and by the end of December and beginning of January the growers will have reviewed how the year went and start to finalize plans for the upcoming growing season (Chase, 4).

At this time they will also be attending conferences to talk to salesmen from seed, fertilizer, and pesticide companies to see what the best products would be. The Mid-Atlantic Fruit and Vegetable Conference occurs in February and includes educational sessions with topics ranging from honeybees for pollination to digital and social marketing, and a large industry trade show (6). However, this conference does not include technology such as artificial intelligence or data analytics software for farmers to use and improve their yields. This conference is where Chase Farms makes their final decision on what seeds, fertilizer, and pesticide to purchase for the year. They typically try out a new type of seed for each of their crops such as Strawberries or Corn, and try out that seed in a field. In March, they set up irrigation systems, plant seeds, and put down fertilizer. In April, they frost-protect any of their crops that are vulnerable to low temperatures, especially their strawberries. They have an alarm system set up that is connected to thermometers in their fields that informs them if the temperature reaches a certain point where they need to frost protect. From April to May they are watching their crops and weeding, fertilizing, and spraying pesticides if necessary. June is when harvesting begins, and the harvesting season goes until the end of October (4).

Chase Farms' mission is to "maintain [their] farm as an agricultural entity for years to come" and to "implement sustainable production of crops" (3). In order to accomplish this they "employ minimum to no till tillage practices whenever possible" which "increases the organic matter in the soil, decreases soil erosion and decreases fuel consumption used in the production of crops" (3). After crops are harvested they "plant cover crops" which are "non cash crops grown for [their] benefit to the soil and ability to suppress weeds and capture nutrients" (3). They employ “many practices recommended by Cornell University” to improve their yields, but do not currently use any data analysis software to analyze or predict future yields (3). They also “employ crop rotation” in order to “[control] insects and disease pressure” (3). They use soil and leaf analysis testing for levels of nutrients in their crops and soils. This enables them to “apply adequate nutrients only as needed” (3). They keep a detailed record of inputs and outputs for each crop and field. Additionally, they keep track of how each seed, fertilizer, and pesticide did and write down which companies they are from so they can capitalize off of the same company next year if those products did well (4). Weather, labor, and competing with grocery stores and large corporate farms are their biggest challenges (4).

2.2 Economic Viability

Currently, policies “governing US agriculture” tend to “favor large over small farms” despite small farms representing around “91% of farms in the US” and are “more productive per unit of land than large farms”(20). Moreover, market conditions “create an economic environment in which farmers must constantly adapt by finding new market niches or increasing the scale of production to remain economically viable” (20). We can see this with Chase Farms implementing U-Pick operations to compete with grocery stores and large farms (3). The current economic model also tends to “ignore costs and benefits of environmental and social goods” that small farms provide such as clean water or local jobs, which results in small farms appearing “less economically efficient than larger farms” (20). Moreover, customers are more likely to buy “cheap food and may not recognize, or be willing to pay for qualitative differences in agricultural products” (20). Larger farms are able to “adopt high tech production practices, along with vertically integrated agricultural firms, and are able to capture the consumer market” with their "lower per-unit costs of production and marketing costs and provide consumers with convenience and consistency at a price below what is economically feasible for small-scale producers" (20). For Chase Farms and other intermediate small farms, they are at a greater risk "in terms of economic viability since they" only rely on income from their farm (3, 20). This reveals an opportunity for the introduction of artificial intelligence and predictive analytics tools into the small intermediate farm sector to improve their economic viability. Small intermediate farms provide "income and economic opportunity for rural residents, communities, and economies", and without supporting small farms those jobs could be eliminated (20).

2.3 Biodiversity

Small farms are furthermore important because many of them "use biologically diversified systems to help decrease economic risks" (20). As a result they "foster habitat diversity, increase non-crop, animal and insect diversity" (20). These "mixed production systems generate more diversity of key nutrients such as zinc, iron, vitamins A and B12, and folate essential for human health" (Fanzo). On a global scale "most vegetables, roots, tubers, pules, [and] fruits… are produced in diverse landscapes" of small scaled farms (11). Moreover, as farm size increases "the diversity of agricultural and nutrient production diminishes" (11). This shows that although larger farms have greater yields and lower prices than small farms, a "large volume of [these] crops… go into processed goods" (Stepien & Maican). The shift towards larger farms puts the biodiversity of land at risk as well as interfering with sustainable farming practices.

2.4 Climate Change

Since agriculture is sensitive to "climatic variability and [because of] the complexity of interactions between agriculture and the global climate system", climate change is a large threat to agricultural systems (Walthall). Rising temperatures and varying precipitation levels are already causing negative effects to agricultural systems (24). Small farms specifically are "highly vulnerable to climate change because most depend on rain-fed agriculture, cultivate marginal areas, and lack access to technical or financial support that could help them invest in more climate-resilient agriculture" (Harvey). Large farms, however, have the financial support enabling them to invest in climate-resilient agriculture. While there are benefits to global warming including "new areas suitable for planting, longer growing periods… [and] improved crop yields", agriculture will suffer in regards to "weather [becoming] more volatile and unpredictable" such as increasing amounts of "droughts, floods, and tornados" (21). For example, Chase Farms along with similar small farms are able to prepare themselves for droughts by setting up irrigation systems, but if droughts become more frequent the costs of watering may become increasingly heavy on them (3). However, larger farms will not be as burdened by this issue and are financially affluent to provide enough water for their crops or buy land in areas with easy access to fresh water. Inversely, flooding is an issue that leads "to increased erosion and decreased soil quality" and affects both large and small farms similarly (24). Climate change and its effects on agriculture shows another opportunity for artificial intelligence to help farms, especially small farms.

2.5 COVID-19 Pandemic

The COVID-19 pandemic has also created problems for farms today. The direct impact on small farms "will actually be much less" because small farms tend to "rely on family labor" meaning they are less likely to have an outbreak of COVID within their farms' work force (Mukhamedjanova). Large farms however rely on labor outside of their family increasing the risk of virus transmission (16). Along with labor being restricted "due to quarantine" and diminishing "from COVID-19 deaths and serious illness", customers "who are fully or partially furloughed" may be unable to buy the same amount of food as they did before due to their loss of income (Stephens). This impacts small farms more than large farms because they rely more on farmer's markets and U-Pick operations in order to compete against large farms. They need to restrict how many people can attend these operations which results in lower earnings. This is seen on Chase Farms as they have restricted the amount of people that can participate in their U-Pick operations and also require masks for customers and workers on their farm (3). Large farms however do not have to worry about their products not selling since they have the option to sell most of their crops at grocery stores. The effects of the pandemic on small farms may "negatively impact agricultural productivity for current and future seasons", further emphasizing the existing threat to their survival (11).

3. Neural Networks in Predictive Analysis for Agriculture

3.1 Overview of Neural Networks and Machine Learning

In the past few years, predictive analysis for farming has risen "as new... [data-intensive] approaches to drive agricultural productivity while minimizing its environmental impact" have been developed (Liakos). As the population of the world continues to grow we will increasingly “need to produce more and better-quality food” in a sustainable way or else we risk “[accelerating] the loss of available arable land, compromising the sustainability of agricultural lands… and causing serious problems for the production-consumption balance” (Loures). This emphasizes the need of “new technologies… to assess their environmental, economic and social impact” such as predictive analysis (15). Predictive analysis for agriculture consists of using machine learning methods to predict yield and other desired outputs. Machine learning (ML) is defined as “the scientific field that gives machines the ability to learn without being strictly programmed” (14). ML models typically consist of a learning process “with the objective to learn from [training data]” (14). This data is in the form of “examples” which could be “a set of attributes… features or variables”(14). These features can be nominal, binary, ordinal, or numeric (14). In the context of applying ML to predict yield for a small farm, the following variables would need to be considered in the ML model (Crane-Droesch): land cover of farm, crop yield of ‘X’ crop, weather, rainfall, fertilizer, pesticides and pest control, machinery used, plant diseases, prices for inputs, and prices for labor. The addition or omission of the variables mentioned above is acceptable and depends on the specific farm that one is looking at when creating a ML model for it.

The “performance” of ML models for a “specific task is measured by a performance metric” which over time is improved (14). Once the learning process is completed, the “trained model can be used to classify, predict, or cluster new testing data” using its experience from training (14). Dimensionality reduction is done on the data in order to provide a “more compact, lower-dimensional representation of a dataset to preserve as much information as possible from the original data set” (14).

There are various different learning models ranging from regression, clustering, bayesian models, and artificial neural networks (ANNs) (14). ANNs are divided into two categories: traditional ANNs and deep ANNs. Traditional ANNs are based on how the human brain functions by creating a "simplified model of the structure of the biological neural network" in which there are multiple layers consisting of nodes (14). The input layer is where the data enters the model, there are then one or more "hidden layers" where the learning actually occurs, and an output layer where the predictions are presented (14). Deep ANNs, or deep learning or deep neural networks, are "composed of… multiple hidden layers" and can be supervised or unsupervised (14).

3.2 Neural Network Applications in Agriculture

In a review of ML models in agriculture, 8 models were reviewed specifically for yield prediction and 3 used neural networks. In the first model, grassland biomass was estimated for "two managed grassland farms in Ireland; Moorepark and Grange" (14). The variables used were "vegetation indices [and] spectral bands of red and NIR" (14). Moorepark had an r-square value of 0.85, and Grange had an r-square value of 0.76. The second model predicted wheat yield using an ANN with "normalized values of on-line predicted soil parameters" as input parameters (14). It resulted in an 81.65% accuracy. The third model was for predicting agricultural yield for crops in general. It used "agriculture data [including] meteorological, environmental, economic, and harvest" resulting in an "1.3% error rate" (14). However, the most impressive ML model is "a novel approach for augmenting parametric statistical models with deep neural networks, which we term semiparametric neural networks (SNN) (8). Used as a crop yield modeling framework, the SNN achieves better out-of-sample predictive performance than anything else yet published"

(8). It used the following variables as inputs: precipitation, air temperature, relative humidity, wind speed, shortwave radiation or daily total solar radiation, growing degree-days, total precipitation over a growing season, latitude/longitude, time, soil percentages of sand, silt, and clay, and proportion irrigated (8).

3.3 User Interface Agriculture Tools using Neural Networks

There are applications that incorporate the predictive properties of neural networks with a user interface that farmers can use. Ag-Analytics uses a combination of public data and user precision agricultural data run through machine learning models and other algorithms to "provide intelligent Forecasting and Prediction tools"(Ag-Analytics). The results are then "displayed and visualized" using a user friendly interface for both the web and mobile (2). There is a free plan for farms to use if they have less than 20 employees and an enterprise version with more custom development and analytics for $0.01 per acre of land per month (2). However, for their crop yield predictor it is only developed for corn, grain, and soybeans for certain counties in the United States.

Cloud Agronomics uses "in-house AI techniques to learn how to turn terabytes of hyperspectral data into accurate… measurements of farm chemistry" (Cloud Agronomics). This helps monitor soil health and determine the "success of restorative agriculture practices" with the goal of optimizing crop yield (5). It has a user friendly interface but not a public free version of their dashboard for farms to try out.

A program from Cornell University called Climate Smart Farming has various tools such as a growing degree day calculator to "predict plant development and pest/disease outbreaks" and a tool to view how the climate has changed and how it will change over time for a chosen county in the northeast (7). The tools are free to use and have tutorial videos explaining how to use each tool, but are not currently used by Chase Farms despite its ease of access (7).

3.4 Customizable Neural Network & Visualization Tools

There are also various technologies that can be used to develop custom neural networks. One of the most prominent tools is TensorFlow. TensorFlow offers easy model building for desktop, mobile, web, and cloud (22). Python, JavaScript, or Swift can be used to develop these models (22). Plotly is another visualization tool that can be used to create custom visualizations for data and ML models. They are also able to "build scalable front ends" for the TensorFlow library (19). Both of these technologies can be combined to create custom ML tools for agricultural systems and build upon already existing models and tools.

Throughout the sources discussed, it is shown that climate change, the COVID-19 pandemic, and the current economic climate will negatively impact small farms more than large farms. Although there is a current shift from small farms to large farms, small farms have proven their importance not only in the economy, by providing jobs for rural communities, but by creating biodiverse fields and produce to feed and provide nutrients needed for the growing population. A way to combat this issue is through predictive analytics and precision farming. The models and user interface tools discussed offer promising results, but more development and outreach is needed to cater and present these tools specifically for small farms. This is the goal of my Yield Predictor web application.

4. Methods & Development

4.1 User Interface Design

After completing the literature review, I began designing the user interface and defining the use cases for the web application. I defined the intended audience of my application to be farms similar to Chase Farms: intermediate family farms "whose operators report farming as their major occupation", that earn between $100,000 and $249,000, and focus on growing crop products and not livestock (20). The farm locations will be restricted to Monroe County, NY which is where Chase is located. The average age of users is expected to be around 55 years of age, and encompass anyone from 50 years and older. The user is expected to have the tech skills of a typical internet user, but not someone who is well versed with technology.

A clean, user friendly interface design is needed to provide clear instructions on how to use the application. The user interface was first planned out with a wireflow diagram. I wanted to give users the ability to choose a crop from a dropdown and predict its yields for the next ten years based on the RCP 4.5 and 8.5 climate scenarios by training a neural network.

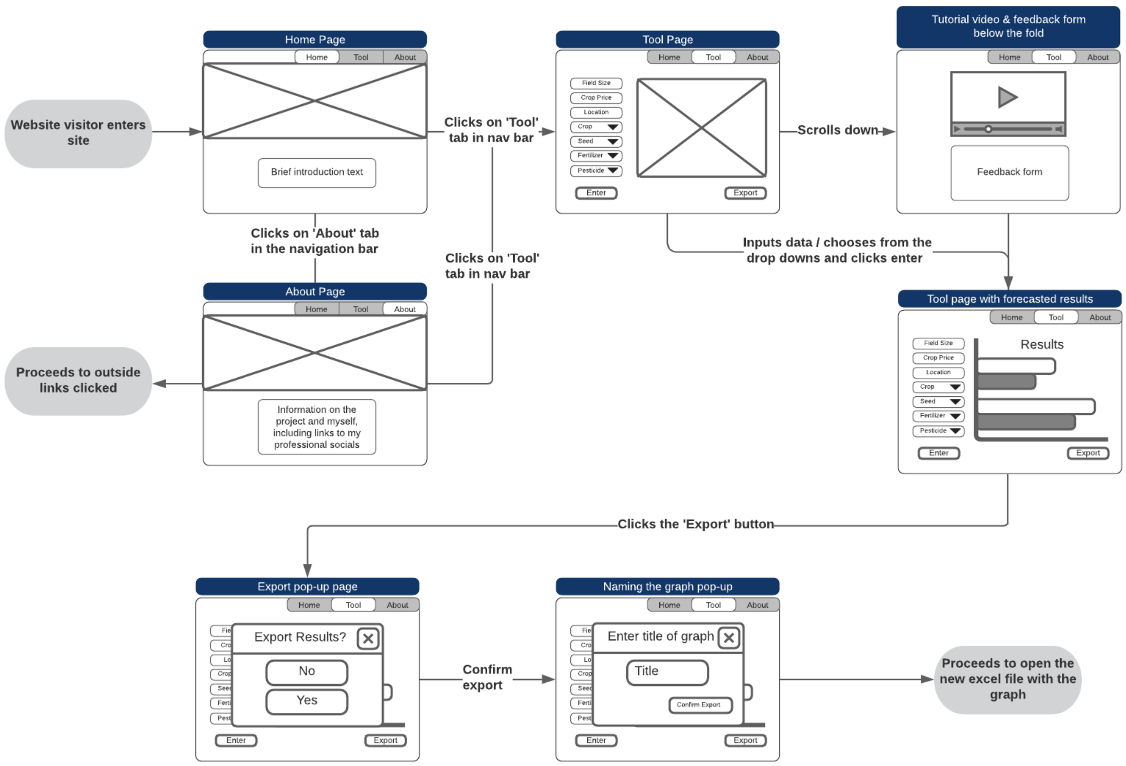

Figure 1. Wireflow Diagram of User Interface for Yield Predictor Web Application

4.2 Collecting Datasets for the Neural Network

The weather data used in the neural network was taken from the Multivariate Adaptive Constructed Analogs (Abatzoglou and Brown). The analogs are a "statistical method for downscaling Global Climate Models from their native coarse resolution to a higher spatial resolution that captures… observed patterns of daily near-surface meteorology" (1). The dataset encompasses the years 2006-2099 which includes future weather data based on two climate scenarios: RCP 4.5 and 8.5. RCPs or Representative Concentration Pathways are a "consistent [set] of projections of only the components of radiative forcing that are meant to serve as input for climate modeling, pattern scaling and atmospheric chemistry modeling" (National Oceanic and Atmospheric Administration, 17). RCP 4.5 is a "stabilization scenario" meaning "the radiative forcing level stabilizes at 4.5 W/m^2 before 2100 by employment of a range of technologies and strategies for reducing greenhouse gas emissions" (17). RCP 8.5 stabilizes at 8.5 W/m^2 before 2100 by "increasing greenhouse gas emissions over time representative for scenarios in the literature leading to high greenhouse gas concentration levels" (National Oceanic and Atmospheric Administration, 18). The data was specifically chosen through their online tool by selecting monthly data for RCP 4.5 and 8.5 for 2006-2099. Then the location of Chase Farms was used as the location point for the data. Finally, the following columns were chosen: tasmax (max temperature), tasmin (min temperature), pr (precipitation), and rsds (downwelling solar radiation).

As for the crop yields, data for strawberries, corn, tomatoes, and snap peas was queried from the United States Department of Agriculture Quick Stats Service (United States Department of Agriculture). These four crops were chosen because they are grown at Chase Farms and had sufficient data for the years 2006 - present. In order to query the yield data, 'Survey' was selected for 'Program', 'Crops' was selected under 'Sector', and 'Field Crops' was selected for 'Group'. The desired crop was chosen under 'Commodity' and 'Yield' was chosen under 'Category'. If the county level data was available for the crop Monroe County was chosen, but if it was unavailable then New York was selected for the state.

Both the crop and weather datasets were downloaded as csv files. The months March through October were selected since that is the growing season. The datasets were then manually combined by adding a crop yield column to the weather data. Separate combined datasets were made for each crop. They were then converted into json files using an online csv to json converter (Data Design Group, Inc.). The json files were then hosted on a github page in order to fetch them from the browser.

4.3 Neural Network Implementation

The app was then developed using HTML, CSS, and Bootstrap for creating the page elements. Then JavaScript was used to implement the functionality of the application. Plotly.js was specifically used for creating the scatterplots. Tensorflow.js was used to create the neural networks to run on the data. In the web application, a sequential Tensorflow model was created. A model is an algorithm that takes an input and produces an output (Google Codelab). A sequential model is where its inputs flow straight down to its output (12). After the model is created the data is then normalized into the numerical range of 0-1 using min-max scaling. The data needs to be normalized because the sequential model is designed to work with small numbers (12). The data is then converted to tensors, which are the primary data structure in TensorFlow. They are N-dimensional data structures that are usually scalars, vectors, or matrices (12).

Now the model is trained. We start by compiling the model using the Adam optimizer and mean squared error for loss. The Adam optimizer is an algorithm that governs the updates to the model as it sees examples (12). It was chosen since it is effective in practice and does not require configuration (12). Mean squared error is used for loss: a function that tells the model how well it is learning each of the data subsets that it is shown (12). Mean squared error is used to compare the predictions made by the model with the true values (12). The batch size is then set to 8 for the number of months per growing season (March-October). The batch size is the number of samples from the training dataset that are used to update the internal model parameters (12). The number of epochs is set to 50. Epochs are the number of times the learning algorithm will work through the entire training dataset (12). The training loop then begins and upon completion it can make predictions based on what it learned. Predictions are done by feeding the model all the rows in the weather and crop dataset that are from the years 2021-2031 which do not have yield data yet. By using those data points as input, the model can then return the predicted yields for those rows. These predicted yields are shown in the scatterplots.

4.4 Web Application Functionality

The web application is accessible to the public from my Yield-Predictor github repository. The Home Page gives an overview of the application, links to all datasets, and defines RCP 4.5 and 8.5 so farmers using the app understand those curves in the scatterplots. The About Page provides the technologies used and gives an overview of neural networks so that users can understand what is going on in the backend and how the yield data is being predicted. The Feedback Form is for users to give feedback on where areas of the application can be improved and if it succeeded or not in helping them plan their growing season.

Figure 2. Application Screen of Yield Predictor Tool

On the Application Page, there are two sections to select a crop and input acres. The first one under the 'Application' header is where farmers can start by entering the amount of acres for a crop they chose from the dropdown. There is also error handling for when the user does not input an amount of acres. Upon hitting the submit button, the neural network will train in the background. Once it has loaded, a scatterplot of predicted yields for the chosen crop will appear on the right. There will be two curves for the climate scenarios. They can hover over each point in order to see the exact number, allowing farmers to see the average and worst cases.

The user can then select another crop and enter the acres for it under the "Choose Crop to Compare" section. Upon submit, another scatterplot will begin to load underneath the previous plot. Once loaded, the user can then compare the predicted yields for the different crops. By looking at both curves in each of the scatterplots for the next ten years they can determine what the best investment would be for the acres they entered. Additionally, they can download each plot as a png file. Previously without this tool our local case study Chase Farms would have to manually go through data from past years for weather and yields in order to make decisions. With this tool they can automate that process, however, more user testing needs to be done for this web application.

5. Future Work & Conclusion

In regard to future work on this application, there are many ways in which it can be further improved. The weather and yield datasets could be expanded to regions beyond Monroe County, New York to enable more farms to try out the application. Additionally, adding more fields to the weather dataset and feeding them into the tensorflow model as inputs will increase the accuracy of the predicted yields. Also, increasing the number of epochs and trying other

Tensorflow models could also optimize the app. An option for farmers to upload their own yield data to be trained in the model could help customize the predicted yields specifically to their own farms. Lastly, since I was unable to present a demo to Chase Farms of the app it would be beneficial to get feedback from numerous small farms in Monroe County and correct any issues that they notice. The feedback form on the application will help accomplish this.

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