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FEASIBILITY OF USING MACHINE LEARNING ALGORITHMS FOR YIELD PREDICTION OF CORN AND SUNFLOWER CROPS BASED ON SEEDING DATE

ALINA DELIA CĂLIN, HOREA-BOGDAN MUREŞAN,
AND ADRIANA MIHAELA COROIU

Abstract. In this research, our objective is to identify the relationship between the date of seeding and the production of corn and sunflower crops. We evaluated the feasibility of using prediction models on a dataset of annual average crop yields and information on plant phenology, from several states of the US. After performing data analysis and preprocessing, we trained a selection of regression models. The best results were obtained for corn using HistGradientRegressor and XGBRegressor with $R^2 = 0.969$ for both algorithms and $MAE\% = 8.945\%$, respectively $MAE\% = 9.423\%$. These results demonstrate a good potential for the problem of yield prediction based on year, state, average plating day, and crop type. This model will be further used, combined with meteorological data, to build an agricultural crop prediction model.

1. Introduction

The problem of increasing crop yields and optimising agricultural production has become more relevant in the context of the growing population worldwide [27]. Recent years have added to this the rapid issues of climate change, which involve water shortages and soil erosion, which affect crop yield (with a projected decrease in corn production of 20-45% by 2100) [3].

Land degradation results in the reduction of available land for crops, unless it is rehabilitated in a sustainable way. Although many agronomic mitigating practises are being proposed, there must be an in-depth analysis as to which is

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the optimal approach, considering that they rely on economic viability, technical complexity, and the perception of the people involved [17]. Furthermore, it seems that several crops (for example corn), when using the *planting green* method, can become vulnerable to losses, while others are more stable (such as soybeans) [25].

Digital farming tools enhanced with artificial intelligence and machine learning models have the potential to help mitigate these issues and bring efficiency to crop management and protection. For example, they can reduce the usage of fungicides by up to 30% and the tank residues by up to 75%, through more precise calculations, thus reducing environmental pollution [28].

Furthermore, machine learning can be used successfully to identify factors that increase crop production under different environmental conditions, as well as model and predict future yields [20]. Many crops have a wide window of ideal plating date (60-90 days). However, crop success can also be influenced by changes in climate or soil composition; therefore, finding optimal planting windows in this context, with its associated risks, is a case-by-case problem for each crop and region [16]. The shortening of the planting window to a shorter optimum must be carried out for each region, according to the characteristics of the climate and hybrid type [5].

In this paper, our objective is to address the feasibility of using regression algorithms to predict corn and sunflower yields, based on the plating date and region, with limited available data. For this, we used historical crop data from several US states that were available online. These crops have been chosen as they are among the most widely cultivated in Romania. As algorithms have proven potential, our aim in future work is to gather Romanian specific crop data and apply machine learning algorithms for a more particular yield prediction.

In the following sections, we will present the related work for this specific problem, as well as the methods used in our experiments and the results obtained.

2. Related work

The problem of optimising yield based on seeding date is approached in many agricultural field researches with specific findings for each location, crop type, and climate particularities.

Patel et al. [24] analyse the effect of different sowing dates for rice crops, emphasising the importance of correlating the sowing date with the most favourable weather conditions of the region. The adaptation of the sowing date and the timing of management practises, as a result of climate change, are also urged by looking at the effects of the sowing date of spring barley and maize in Germany and Poland [18].

For summer maize in irrigated crops, from the semi-arid Guanzhong region of China, an optimum planting date and water requirements for increased yield were modelled based on crop phenology, grain yield, above-ground biomass and leaf area index, using the Decision Support System for Agro Technology Transfer (DSSAT) Version 4.6 [26]. The results were statistically calculated on the observed data, obtaining a normalised root mean square error (nRMSE) of 9.91%, and $R^2 = 0.62$. An other study referring to summer maize in China regions argues that, given specific conditions of extreme heat, delaying the sowing date would improve the maize yield by 2–25% [15]. A late sowing date appears to be the best for overall yields for irrigated regions in the Mediterranean also [19], and a mid-to-late for the North China Plain [30].

When cultivating sunflower in Mediteranean climate conditions [12], the most effective was a later date, under rainfed conditions, but an early date in regions with little water availability. A study carried out on sunflower crops in Punjab, Pakistan [29], recommends earlier sowing dates for spring sowing and delayed sowing dates for fall, to mitigate the warming effects of climate change and ensure sustainable productivity.

A limitation of the studies presented above is that they only use a narrow data range of 1 to 3 years and a few plantations (1-5), which means that annual seasonal meteorological variations are not always accounted for [23]. Additionally, regional characteristics (soil type, climate) for the specific hybrids [2] will have an influence on yield, but field data is limited to one or two regions in most studies.

In this sense, machine learning can help model these problems, using different algorithms and techniques for data preprocessing and augmentation, and may leverage the effect of a single independent variable, which may not be obvious, in contrast to statistical models [20]. Algorithms such as Artificial Neural Networks, Support Vector Regression, k-Nearest Neighbour, Multiple Linear Regression, M5-Prime have been successfully applied with accurate results in estimating crop yield [13]. The accuracy metrics that are generally used for validation are Root Mean Square Error (RMS), Root Relative Square Error (RRSE), Normalised Mean Absolute Error (MAE) and Correlation Factor (R) or Coefficient of Determination (R^2 - basically, the square of the correlation coefficient) [7].

Yield prediction is a sub-field of crop management, and most research papers related to machine learning focus geographically on China, USA, India, and Brazil [4], with limited interest in European countries, especially Romania.

Alam et al. [1] use regression to determine the correlation between sowing dates and maize grain yield in Bangladesh, obtaining $R^2 = 0.972$. In Mourtzini et al. [20] process crop information for maize (n = 17,013) and soybean (n = 24,848) (including yield, crop management), and weather data involving 28 US states, between 2014 and 2018. The data was split in training (80%) and test (20%). The extreme gradient boosting (XGBoost) algorithm was trained to predict the yield based on the previous variables, resulting in a mean absolute error (MAE) of 4.7 with $R^2 = 0.94$ for maize, and MAE=6.4 with $R^2 = 0.92$ for soybean. Evaluation was performed using ten-fold cross-validation. A similar study uses the functional gradient descent algorithm on the data from the US corn and soybean, with a split of 85% training and 15% test [21]. The model predicts that early sowing dates can increase soybean yield by 10% in most US states, in the simulated context of climate change with a 30% reduction in precipitation during the summer months.

In the case of wheat yield prediction in Australia, Random Forest and Multiple Linear Regression models are used with meteorological data, identifying drought seasons as the main factor in yield losses [10]. The forecasts at 35 days before harvest were r = 0.85, MAPE = 17.6%, and 60 days before harvest r = 0.62, MAPE = 27.1%.

For the prediction of massive crop yields, Gonzalez-Sanchez et al. [13] analyse several algorithms on ten crop datasets. The M5-Prime Regression Trees and the k-Nearest Neighbour obtain the lowest average RMSE errors (5.14 and 4.91), the lowest average MAE errors (18.12% and 19.42%), and the highest average correlation (0.41 and 0.42), followed by Multiple Linear Regression, Multilayer Perceptron Neural Networks, and Support Vector Regression. In another study, Deshmukh et al. [9] analyse several algorithms (Random Forest, KNN, Naïve Bayes, XGBoost) for the top three crop recommendations for an optimised yield, of which XGBoost provides the best results.

3. Methods

Given the variety of approaches and results for different algorithms, we have selected the best potential for our specific data. Our approach focuses on the two types of crops: corn and sunflower.

3.1. **Data preprocessing.** The data have been extracted from the US National Agricultural Statistics Service [31]. Although there are sufficient entries (with $n = 88808$ data instances) and many machine learning approaches for the corn data, as presented above, the sunflower data are limited to $n = 312$ instances for the sowing date and the corresponding yield, which is not sufficient for the accurate training of the regression model. Therefore, data preprocessing involved first the aggregation of yield data (in lb/ac) for each state and year with the seeding date for both crops. The information available on the planting was in the format of percentage of the crop planted each week of the year. Using this information, a new feature was created as the average planting day of the year (D or AVGWeek), calculated as a weighted average based on the weekly percentages, with d_i the day of seeding and w_i the cumulative percentage planted up to that date d_i, with $w_0 = 0$ (see Equation (1) below). The resulting date was then translated into the day of year (with January 1 being the first day of year).

$$D = \frac{1}{n} \sum_{i=1}^{n} d_i (w_i - w_{i-1}) \tag{1}$$

Data cleaning was also performed to remove inconsistent field values or incomplete entries. As a result, we obtained $n = 88808$ instances for corn, for several years from 1979 to 2022. This is described in Figure 1.

For sunflower, given the available yield data, the information that was not available on the seeding date was completed using the forward fill method, which means similar planting dates for the same state, thus resulting $n = 1108$ instances, for several years in the range 1950 to 2021. The data description plots for sunflower are shown in Figure 2.

As a result, for each crop dataset, an entry contains 5 features: the year (type int), the state ANSI (type int), the crop type (Irrigated, Non-irrigated and Total, which have been encoded using the factorise method), the yield (of type float) and the planting day of year (of type float). From these data, we can extract and visualise the plating day-of-year interval window used in each state, across the reference years. In Figure 3, it can be observed that there are fewer states available for the sunflower dataset. The planting days are from day 80 to day 170 for corn and from day 135 to day 170 for sunflower, with the width of the planting windows ranging from 15 to 40 days.

Furthermore, the correlation matrices were also calculated and are shown in Figures 4 and 5. For corn, we note a 0.22 positive correlation between the yield and year, and a negative correlation between crop type and yield.

In the case of sunflower, we observe a 0.57 positive correlation between year and yield value, and 0.25 between year and average planting day of year. The correlation between the yield value and the average day of planting is 0.13, and there is a negative correlation between the type of crop and the yield value.

Given the correlation in both datasets between year and yield, we have analysed the line plots of crop yield for each state per year, in Figure 6. It can be observed that the overall tendency is that yield increases over time. As this might be due to several factors, including technological agricultural advancements (availability of machinery, fertilisers, pesticides, new hybrids,

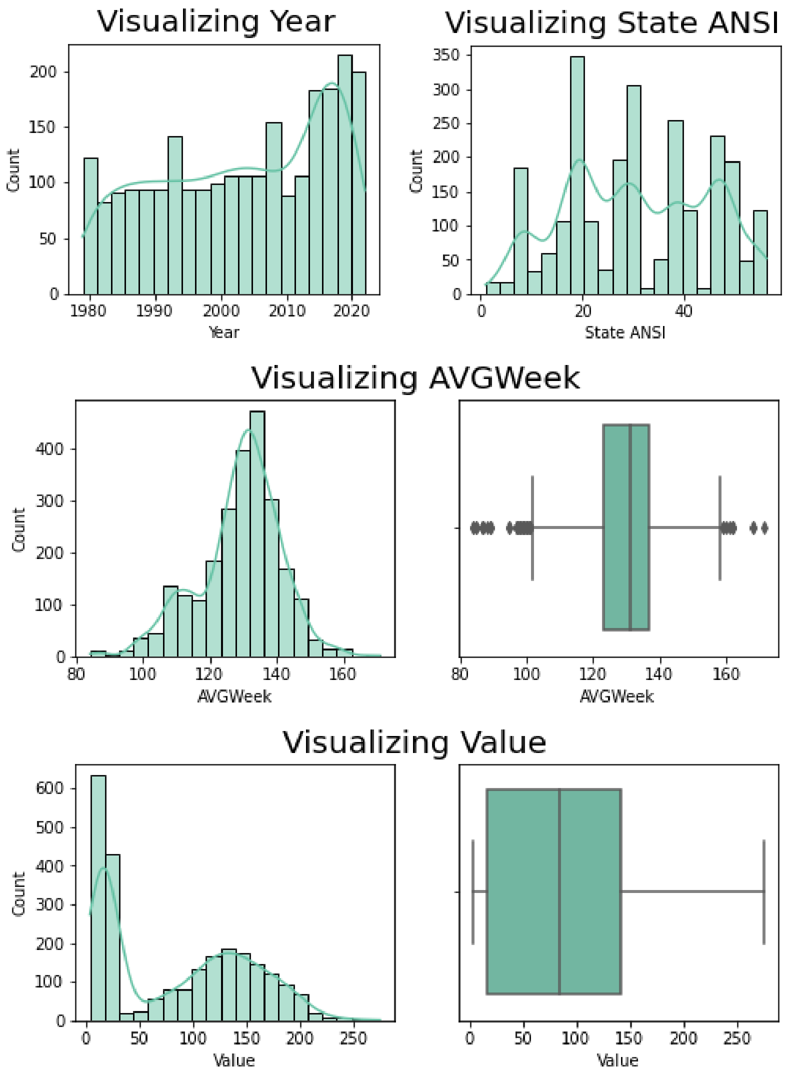


FIGURE 1. Feature description for the corn crop dataset features: Year, State ANSI (or state numerical code), AVGWeek (the average plating day of year) and Value (the yield value).

etc.), we decided to perform two experiments: one in which all features are involved in yield prediction, and one in which the year feature is removed, remaining only state code, crop type, and average plating day to be considered in the prediction of the crop yield.

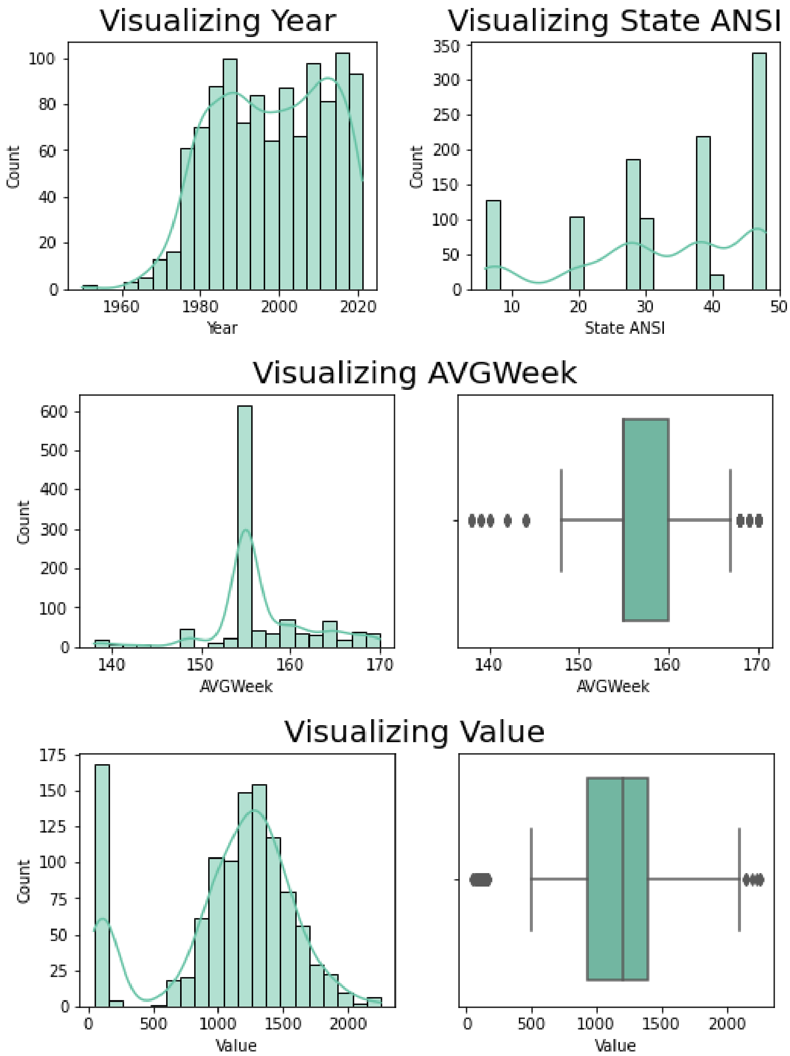


FIGURE 2. Feature description for the sunflower crop dataset: Year, State ANSI (or state numerical code), AVGWeek (the average plating day of year) and Value (the yield value).

3.2. **Models training.** Based on the literature review, we have selected several regression algorithms that are appropriate for our specific problem.

3.2.1. *DecisionTreeRegressor.* A Decision Tree is built in the form of a tree-like hierarchical structure, containing internal nodes (or decision nodes) and

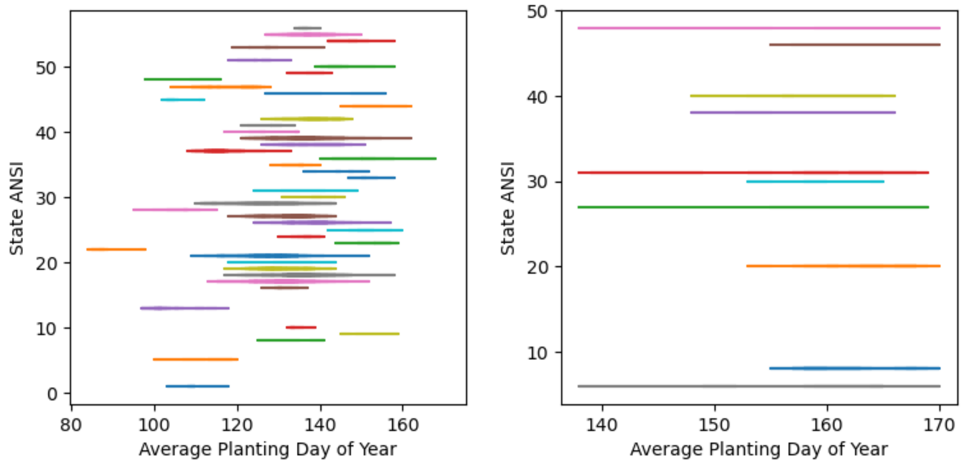


FIGURE 3. The average planting day of year window in each state (based on state ANSI) for corn (left) and sunflower(right).

FIGURE 4. Correlation heat map for the corn crop dataset

leaf nodes (or prediction nodes). The height and width of such a tree depend on the data characteristics, amount, and algorithm configuration. In the case

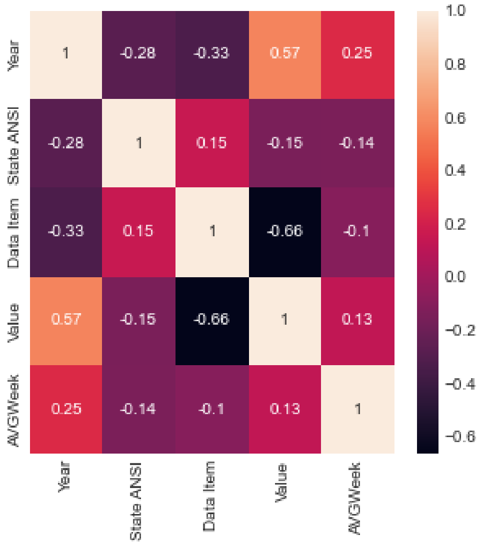


FIGURE 5. Correlation heat map for the sunflower crop dataset

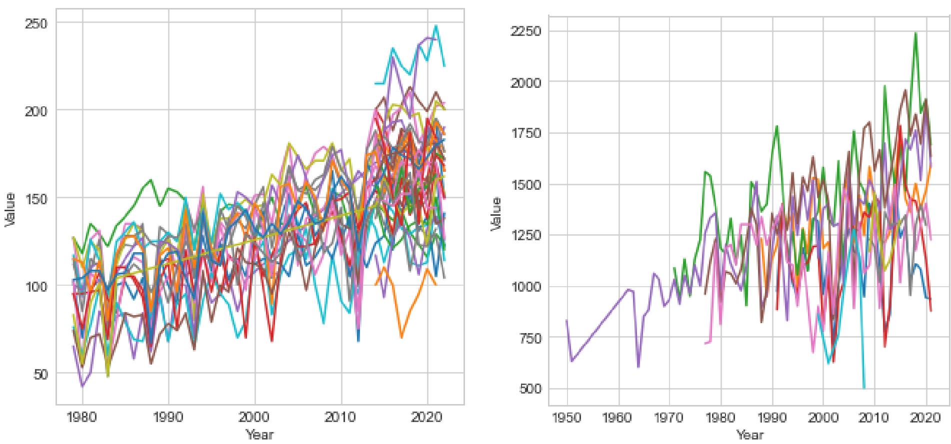


FIGURE 6. Yield value per year for each state for corn (left) and sunflower (right).

of prediction, we use an input x_i to go down the tree using decision nodes, up to a leaf that contains the predicted y_i value [8].

3.2.2. *RandomForestRegressor.* Random forest is an algorithm that groups an ensemble of growing decision trees, depending on a random vector $f(\phi)$. Thus, the predictions are performed by aggregating the predictions of all the decision trees $h(x, \phi)$ [14].

3.2.3. *HistGradientBoostingRegressor.* The Histogram-based Gradient Boosting Regression Tree also uses ensemble decision trees. It improves performance by adding new corrective models in a greedy stepwise manner, with the aim of reducing the square error loss function until it is acceptable [11]. The histogram is an efficient data structure used by the tree-building algorithm to accelerate the process.

3.2.4. *XGBRegressor.* The XGBoost is a scalable end-to-end Gradient Boosting Tree system that is using cache access patterns, data compression, and block sharding to optimise resource use [6].

3.2.5. *Models training and hyperparameters tuning.* The algorithms presented above have been trained and tested using a data split of 20% for testing and 80% for training. Next, the parameters were fine-tuned; for XGBRegressor the number of estimators was set to 500, max depth to 8 and learning rate to 0.1. HistGradientBoostingRegressor used a learning rate of 0.01, with the maximum iterations set to 1000 and the loss function Poisson. RandomForestRegressor was set to use 25 estimators with a maximum of 4 features and at most 700 leaf nodes, with a random state of 45. For DecisionTreeRegressor the max depth was set to 10, the other parameters being as default by the Sklearn Python library implementation.

3.3. **Models evaluation.** For the model evaluation we used the k-fold cross-validation with $k = 10$. We note the mean absolute error (MAE), which is calculated as an average of the absolute prediction error as in Equation (2), where y_i is the observed value and $\hat{y}_i$ is the predicted value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

Another metric used is the coefficient of determination R^2, which represents how much of the variation in the y values (yield in our case) is taken into account by the involved features, computed as in Equation (3), where $\bar{y}$ is the mean of the observed values [22].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

We also computed MAE%, computed by dividing MAE by the average yield value for corn and sunflower, respectively, as described by Formula (4):

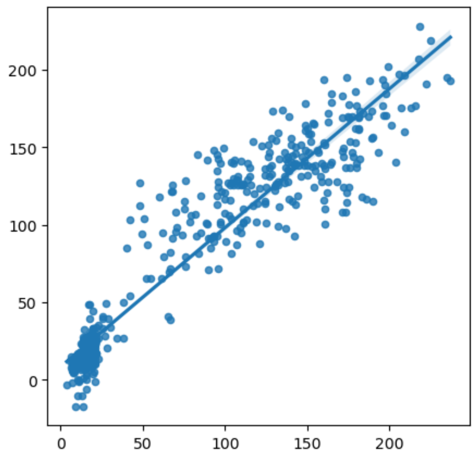
$$MAE\% = \frac{MAE}{\frac{1}{n}\sum_{i=1}^{n} y_i} * 100 \tag{4}$$

4. Results and Discussion

The results obtained by each model are presented in Table 1 below, in which we provide the values for the mean (M) and standard deviation (SD), for the datasets including all features or without year (w/t year). The best yield prediction was obtained by the XGBRegressor (with $R^2 = 0.969$ for corn and $R^2 = 0.905$ for sunflower) and HistGradientBoostingRegressor ($R^2 = 0.969$, for corn and $R^2 = 0.884$ for sunflower), when all features were included.

While the R^2 score is lower when the year is removed, it is still greater than 0.9 for corn, with the best result for sunflower being 0.815.

The prediction plot is visible in Figure 7 for the corn dataset, including both experiments: using all features, and when removing the input feature that represents the year. Figure 8 presents the regression plot for sunflower with all features and, respectively, without year. In both figures, the x axis represents the actual yield, and the y axis is the predicted yield.



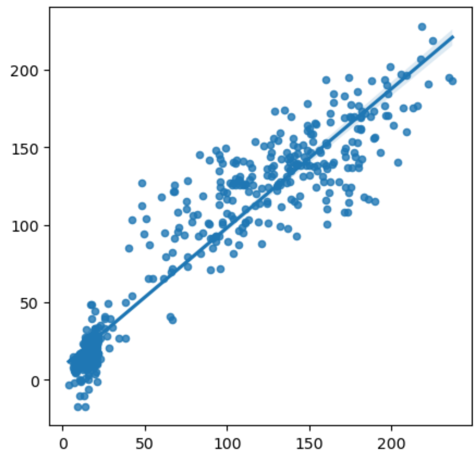


Figure 7. Corn crop yield prediction plot using all features (left), and without year (right), using the XGBRegressor model

Based on these results, we can state that the algorithms used in the prediction reveal models with a good correlation of the selected characteristics (year, state, plantation date, type of crop) with yield. From these, the year and the planting day appear to be both relevant features in predicting the yield for a

TABLE 1. The results on yield prediction for each algorithm

	XGBRegressor				
	R^2 M	R^2 SD	MAE M	MAE SD	MAE%
Corn	0.969	0.006	7.864	0.634	9.423
Sunflower	0.905	0.028	106.778	10.473	9.768
Corn (w/t Year)	0.907	0.013	14.299	0.976	17.134
Sunflower (w/t Year)	0.815	0.047	156.957	13.515	14.359

	HistGradientBoostingRegressor				
	R^2 M	R^2 SD	MAE M	MAE SD	MAE%
Corn	0.969	0.006	7.465	0.619	8.945
Sunflower	0.883	0.032	119.289	10.838	10.913
Corn (w/t Year)	0.909	0.015	12.736	1.187	15.261
Sunflower (w/t Year)	0.797	0.047	167.133	13.687	15.290

	DecisionTreeRegressor				
	R^2 M	R^2 SD	MAE M	MAE SD	MAE%
Corn	0.940	0.010	10.009	0.776	11.993
Sunflower	0.861	0.039	124.517	13.345	11.391
Corn (w/t Year)	0.870	0.021	14.587	1.139	17.479
Sunflower (w/t Year)	0.753	0.056	180.455	15.437	16.509

	RandomForestRegressor				
	R^2 M	R^2 SD	MAE M	MAE SD	MAE%
Corn	0.959	0.007	8.483	0.700	10.164
Sunflower	0.905	0.026	107.432	10.457	9.828
Corn (w/t Year)	0.891	0.018	13.779	1.235	16.510
Sunflower (w/t Year)	0.794	0.043	168.073	13.256	15.376

specific geographical location (state). These are in agreement with the results obtained and the findings described in the state-of-the-art literature presented in Section 2.

We also note the high metrics obtained for predicting the sunflower crop yield, where the available data were limited, which means that the total number of instances was $n = 1108$. Of these only $n = 312$ contained complete information regarding the plating day, the others were completed by our algorithms in the preprocessing phase. This is an important finding, because no other study has performed similar experiments on such a small number of

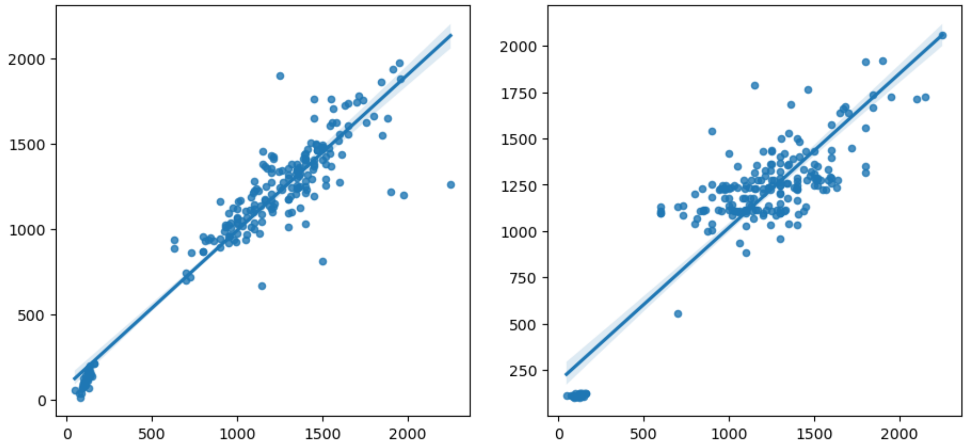


FIGURE 8. Sunflower crop yield prediction plot with all features (left), and without year (right), using the XGBRegressor model

instances for a crop dataset, considering our goal is to train models on Romanian crop datasets also, for which the data are being collected, and are expected to be reduced in size. This is due to the fact that the collection is not yet being centralised by a national statistical organisation, but privately gathered by smaller independent agricultural entities for their own research and seasonal activity.

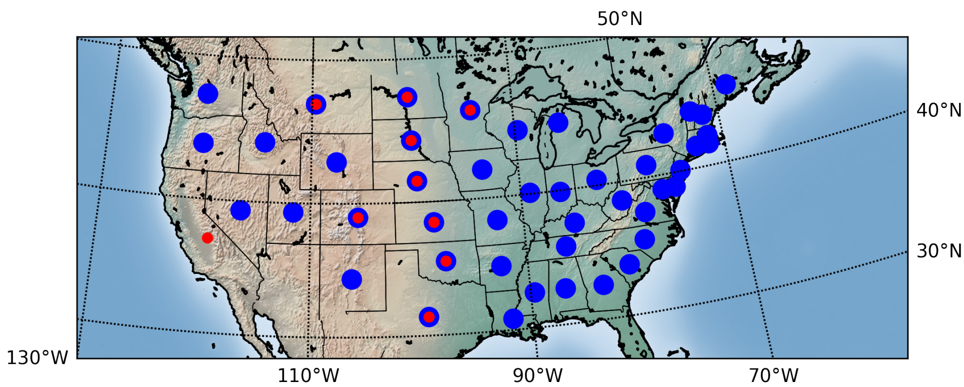


FIGURE 9. Geographical location of the available data. Blue dots represent states with corn crop data. Red dots are states with sunflower crop data.

5. Conclusions and future work

In this paper, we analysed two crop datasets for the purpose of predicting the yield based on the plating date. We obtained the best score of $R^2 = 0.969$ for the corn dataset ($n = 88808$) and $R^2 = 0.905$ for the sunflower dataset ($n = 1108$), using XGBRegressor.

To better isolate the effect of the plating date from other factors, such as technical advances throughout the years (especially given the wide range of years of available data and the tendency of yield increase throughout the years), we repeated the experiments without the year component. In this case, the best results were obtained using the HistGradientBoostingRegressor for the corn dataset ($R^2 = 0.909$).

Given the results obtained, we conclude that the plating day of year has a significant influence on crop yield prediction, for both corn and sunflower datasets. We also note that it is feasible to use regression algorithms to successfully predict crop yield even in cases where the available data are limited (as in the case of the sunflower crop), using adequate data preprocessing techniques. This finding is relevant for our planned work, because we expect the initial available data to be reduced and perhaps incomplete.

As next steps, we aim to collect several crop data sets specific for the Romanian agricultural sector and train predictive models adapted to geographical and crop particularities.

Also, considering the literature in the field stating that the seeding date might be in itself influenced by specific climate changes or meteorological seasonal variations, further work also involves correlating these parameters, in the context of global warming and its effects in agriculture.

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Babes-Bolyai University, Kogalniceanu 1, Cluj-Napoca
Email address: alina.calin@ubbcluj.ro

Email address: horea.muresan@ubbcluj.ro

Email address: adriana.coroiu@ubbcluj.ro