Crop yield predictions by regression statistical models

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***Abstract***

Regression analysis is a statistical technique used to estimate the relationship between variables with a cause-and-effect connection. Predicting crop yield in the current growing season is crucial for farmers, policy makers, and food processing plants to make informed decisions and maximize income. Reliable prediction tools offer valuable insights for managing agricultural products and guide the adoption of appropriate strategies. However, it is important to consider the limitations and assumptions associated with regression models, such as linearity assumptions and the presence of outliers, to ensure their proper application. Research contributes to the existing knowledge on regression modeling for prediction tasks in the agricultural domain. By evaluating different regression algorithms and their performance metrics, practitioners and researchers gain a solid foundation for selecting and implementing suitable regression models in predictive analytics. Our results demonstrate that regression models are powerful tools for accurate predictions of target variables. Performance evaluation metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R²) coefficient provide a comprehensive assessment of the model's predictive ability and overall fit. The challenge in creating forecasting models lies in selecting the appropriate independent variables, which requires a deep understanding of the research subject. Regression analysis provides precise quantitative information that managers can rely on for decision-making and problem-solving. It offers a structured approach to data analysis, emphasizing its importance in research and decision-making processes. In this, regression analysis plays a significant role in predicting crop yield and enabling informed decision-making in the agricultural sector. By considering the limitations and assumptions of regression models, practitioners can leverage their predictive capabilities to generate reliable estimates. The comprehensive evaluation of different regression algorithms and their performance metrics presented in this research serves as a valuable resource for practitioners and researchers seeking to enhance their predictive analytics capabilities in the agricultural domain.

**Keywords**: Regression analysis; prediction tool; crop; coefficient; data

1. **Introduction**

Regression is a statistical approach for simulating the relationship between a variety of independent variables and a dependent variable. It helps to identify the relationship between variations in the independent factors and variations in the dependent variable. It is widely used in various fields, including economics, finance, social sciences, and machine learning. The dependent variable in marketing applications is often the objective we're aiming to achieve, and the independent variables are potential means by which we can achieve that objective. Regression analysis is one of the most insightful methods available. Regression analysis has the following main advantages:

1. State whether a link between independent and dependent variables is meaningful.

2. Describe how powerfully certain independent variables have an impact on the dependent variable.

3. Assume the future.

Agricultural researchers can benefit in a variety of ways from understanding how independent variables affect dependent variables. For instance, knowing that promotional activities considerably enhance agricultural yield can assist target spending. In agriculture, understanding the relative strength of effects can be helpful in determining issues like whether productions are more dependent on weather or other inputs. Additionally, regression analysis enables us to examine the effects of factors assessed at various scales, such as the impact of changing weather patterns, various crop kinds, seasons, sowing dates, and spatial distribution.

Regression models are used to predict the yield of crops including cotton, wheat, and maize based on soil weather and crop characteristics. A few (linear and nonlinear) techniques for estimating crop yield are can be correlated [1]. The comparison is performed using the best property subset for each method identified using percentage split validation and an entire algorithm from the preparation dataset. The technique builds the models using the oldest samples and then searches the training datasets for the best attribute subset. Unseen samples make up the test datasets, where performance is assessed. The most well-known information-driven techniques for agricultural yield prediction, including regression trees, stepwise linear regression, multiple linear regression, and neural networks, were evaluated. Given that the Ordinary Least Square (OLS) estimation is a popular technique for predicting crop output, [2] researchers take the linear regression model into consideration. With a greater R', the autoregressive model outperformed the OLS in this case. According to the study, precipitation and NDVI had a greater impact on the crop output in Iowa than temperature did.

Regression models, time series models, and probabilistic models are only a few of the forecasting methods covered by Ramasubramanian academics in the field of agriculture. There are three types of regression models: a logistic regression model for qualitative response variables, a multiple linear regression model for crop production projections, and a multiple linear regression model based on weather indicators for agricultural insect count. For the production of crops, an exponential smoothing model and an auto regressive integrated moving average model are both utilized in time series models. Markov Chain Model is used in probabilistic models to anticipate agricultural yield.

Regression models are used to predict the values of the dependent variable based on the values of the independent variables. This predictive capability is valuable for forecasting future outcomes and making informed decisions. It explains the relationship between the dependent variable and the independent variables. They provide light on the variables that affect the dependent variable as well as the strength and direction of their effects. Enable researchers and analysts to control for the effects of other variables and isolate the impact of specific factors. By accounting for confounding variables, regression models allow for a clearer understanding of causal relationships.

1. **Types of Regression Models**

There are various types of regression models, each suited for different scenarios and data types. Some commonly used regression models include:

1. Simple Linear Regression: This model involves a single independent variable and a linear relationship with the dependent variable. It assumes a straight-line relationship between the variables.

The link between a single independent variable (X) and a dependent variable (Y) is modeled using simple linear regression, a statistical approach. It presumes that the two variables have a linear relationship, which would suggest that a change in X would result in a corresponding change in Y. The equation is a simple linear regression:

Y = β₀ + β₁X + ε

where:

- Y is the dependent variable

- X is the independent variable

- β₀ is the intercept (the value of Y when X is 0)

- β₁ is the slope (the change in Y for a one-unit change in X)

- ε is the error term (represents the random variability or unexplained factors)

1. Multiple Linear Regression: In this model, there are multiple independent variables influencing the dependent variable. It allows for the analysis of the combined effects of multiple factors. In order to expand on the idea of basic linear regression, multiple linear regression takes into account the relationship between a dependent variable (Y) and two or more independent variables (X1, X2,..., Xp). It makes the assumption that the dependent variable and the independent variables have a linear relationship, enabling the analysis of numerous factors at once. The expression for the multiple linear regression model is:

Y = β₀ + β₁X₁ + β₂X₂ + ... + βₚXₚ + ε

where:

- Y is the dependent variable

- X₁, X₂, ..., Xₚ are the independent variables

- β₀ is the intercept (the value of Y when all X variables are 0)

- β₁, β₂, ..., βₚ are the slopes (representing the change in Y for a one-unit change in each X variable)

- ε is the error term (representing the random variability or unexplained factors)

1. Polynomial Regression: This model extends simple linear regression by including polynomial terms of the independent variable. It can capture nonlinear relationships between variables. In order to model nonlinear correlations between the dependent variable (Y) and the independent variable (X), polynomial regression is an extension of linear regression. It involves fitting the data to a polynomial function of the independent variable. Higher-order polynomial terms can be used into polynomial regression to capture more intricate patterns and curves in the data.

The polynomial regression model can be expressed as:

Y = β₀ + β₁X + β₂X² + ... + βₚXᵖ + ε

where:

- Y is the dependent variable

- X is the independent variable

- X², X³, ..., Xᵖ are the higher-order polynomial terms (squared, cubed, etc.)

- β₀, β₁, β₂, ..., βₚ are the coefficients for each term

- ε is the error term (representing the random variability or unexplained factors)

1. Logistic Regression: An analysis of the relationship between a binary or categorical dependent variable and more than one independent variable is done by the statistical modeling technique known as logistic regression. Unlike logistic regression, which is used to predict binary outcomes, linear regression uses continuous dependant variables.

The logistic function, also referred to as the sigmoid function, is used by the logistic regression model to convert the linear combination of independent variables into a probability value between 0 and 1. The possibility that the dependent variable falls into a particular category is represented by this probability. The logistic regression model can be expressed as:

p = 1 / (1 + exp(-(β₀ + β₁X₁ + β₂X₂ + ... + βₚXₚ)))

where:

- p is the probability of the dependent variable belonging to a particular category

- β₀, β₁, β₂, ..., βₚ are the coefficients for each independent variable

- X₁, X₂, ..., Xₚ are the independent variables

5. Ridge regression: Ridge regression also known as Tikhonov regularization, adds a penalty term to the least squares objective function in linear regression. The penalty term is a scaled version of the sum of squared coefficients, multiplied by a regularization parameter (λ). The ridge regression objective function can be expressed as:

minimize: RSS + λ∑(βᵢ²)

where:

- RSS is the residual sum of squares, representing the difference between the predicted values and the actual values.

- λ (lambda) is the adjusts the coefficients' amount of shrinkage with a regularization parameter.

- ∑(βᵢ²) is the sum of squared coefficients.

The magnitude of the coefficients, particularly the less significant ones, is reduced but not entirely eliminated by the ridge regression penalty term. In ridge regression, all variables are included in the model even though their coefficients are shrinking toward zero, hence variable selection is not performed.

6. Lasso Regression: Another regularization method that includes a penalty term in the least squares objective function is known as lasso regression (short for "least absolute shrinkage and selection operator"). However, unlike ridge regression, lasso regression uses the sum of the absolute values of the coefficients multiplied by the regularization parameter (λ) as the penalty term. The lasso regression objective function can be expressed as:

minimize: RSS + λ∑|βᵢ|

where:

- RSS stands for residual sum of squares, which depicts the discrepancy between the expected and actual numbers.

- λ (lambda) The regularization parameter regulates how much shrinkage is done to the coefficients.

- ∑|βᵢ| is the sum of absolute values of the coefficients.

Lasso regression provides the ability to do both regularization and variable selection. It has the ability to make unnecessary or minor variables' coefficients equal to zero, essentially removing them from the model. Therefore, lasso regression can be useful in situations where feature selection is desirable.

3. Key Differences: The main differences between ridge regression and lasso regression are:

a) Penalty term: While lasso regression utilizes the sum of the absolute values of the coefficients, ridge regression uses the sum of squared coefficients as the penalty term.

b) Variable selection: With ridge regression, all variables are kept in the model without any variable selection; instead, their coefficients are reduced. Contrarily, Lasso regression carries out variable selection by setting the coefficients of less significant variables to zero.

c) Solution: Ridge regression has a closed-form solution and can be solved analytically. Lasso regression does not have a closed-form solution, and various optimization algorithms like coordinate descent or least angle regression (LARS) are used to find the optimal solution.

d) Sparsity: Lasso regression can produce sparse models with fewer non-zero coefficients, making it useful when interpretability and feature selection are important. Ridge regression generally does not yield sparse models, as the coefficients are only shrunk towards zero, but not eliminated completely.

e) Tuning parameter: Both ridge regression and lasso regression have a regularization parameter (λ) that controls the amount of shrinkage. However, λ has a different impact on the coefficients in each method. In ridge regression, higher values of λ lead to more shrinkage of the coefficients, while in lasso regression, higher values of λ can drive more coefficients to zero.

7. Time series: In time series regression, the primary objective is to model and forecast the behavior of the dependent variable based on the values of the independent variables and their historical patterns. The independent variables can include lagged values of the dependent variable itself, as well as other exogenous variables that may influence the time series.

Data required for regression analysis

Estimate and Specify the model

To test the assumptions

Interpretation

Validation

Use the regression model

Fig. 1 Steps of regression analysis

The time series regression model can be expressed as:

Yₜ = β₀ + β₁X₁ₜ + β₂X₂ₜ + ... + βₚXₚₜ + εₜ

where:

- Yₜ represents the value of the dependent variable at time t

- X₁ₜ, X₂ₜ, ..., Xₚₜ represent the values of the independent variables at time t

- β₀, β₁, β₂, ..., βₚ are the coefficients associated with each independent variable

- εₜ represents the error term or residual at time t

**3. Yield prediction through regression model**

Regression models' layout for estimating agricultural yield: The general method used to construct the regression models for agricultural yield prediction is described in this study. Regression analysis is widely used for prediction since it provides a predicted item as a function of the dependent entities. It provides correlations between independent and dependent variables in some circumstances [3]. The procedures for creating a regression model to forecast crop yield.

Start

Gathering and processing the raw data

Training and test the data set

Train the regression model and apply trained model on test set

Compute R2, RMSE and MPPE for model

Check if RMSE, MPPE is lowest and R2 is highest

 No

 Yes

Stop

Fig. 2: Regression methodology for crop yield prediction

A regression model as a tool for prediction and chose a few key elements in yield production [4]. The input variables for the regression model can be the features and data taken together. In a similar vein, the yield's best regression model is identified. To deal with potential root mean square and R2 statistics value estimates, each model is performed several times. The survey's best regression model is used to forecast the generation of the various crops throughout a range of years. The results show that the suggested regression model is an effective way to predict yield production. The results of various models are compared using the root mean square, R2 statistics, and percentage prediction error. One with lower values for Root Mean Square, percentage prediction error, and R2 statistics is the best model for forecasting crop yields.

In order to forecast the amount of rainfall in the region of Myanmar, researchers take into account the Polynomial Regression Model (1.1PR) [5]. The authors used second-arrange 1.1PR to develop a prediction forecast model with 15 predictors. A few tests have shown that the predicted precipitation swn is rather close to the actual characteristics. Four indicators were used to develop the SJ.1R expectation model. The model's outputs were put to use in the territories, such as in water management and repository control, harvest planning, and yield prediction. Helping with farm management and water management is the main goal of forecast model improvement. All potential subsets of predictors have been studied in the application of multiple polynomial regression, which only uses test data from 2006. The authors present evidence that 1.1PR outperforms MLR. Researchers expand on traditional regression neural networks [6]. The Conformal Prediction (CF) framework for predicting tomato output in a greenhouse incorporates the Vapor Pressure Deficit (VPD), CO2, radiation, and temperature. This technique required the utilization of over 60,000 records.

The three main types of statistical models are panel models based on spatiotemporal variation data, cross-section models based on spatial variation data, and time-series models based on time series data from one specific point or region [7]. Recent literature has examined how well the three strategies indicated above perform, however the findings are not conclusive. The various statistical models showed that the differences in the results are not always obvious based on data of crop yields, including maize, soybean, and cotton, as well as climate variables in America [8]. However, the panel regression method to demonstrate that time-series models do not adequately capture the robustness of corn production responses to temperature in Sub-Saharan Africa [9]. The error of the panel regression method is lower than the error of the time-series model [10].

Certain fixed assumptions are made by time-series models, such as the notion that the historical relationship between agricultural yields and climate will remain constant in the future [11]. Time-series models hardly ever take climate change adaptations into account, with the exception of those for extreme weather events [12]. Cross-section models assess various geographical conditions while taking into account all of the adaptations in various areas and climatic variables [13]. Panel models, which combine temporal data from many locations into one study, should have a similar number of adaptations as the other two approaches. The exact amount of adaptation, however, depends on the annual fluctuations within sites as opposed to annual differences across sites [14].

Researchers have shown that, provided that these coefficients are constrained away from zero at a specific rate, the LASSO requires a specific situation in order to select the optimal set of nonzero true coefficients [15]. As a result, the LASSO generally lacks selection consistency, which is consistent with the findings of reference [16]. Due to the shrinkage effect, LASSO chooses more predictive variables than there are actual variables, yet it still manages to reach an optimality in the minimax sense, resulting in good prediction accuracy. For a few specific LASSO minimax rates in high-dimensional models, see reference [17]. Reference [18] suggested utilizing the two-stage adaptive Lasso under the restricted eigenvalue constraints for consistent model selection in linear and Gaussian graphical models, reference [19] proved that even when p > n, partial orthogonality criteria can be met when using marginal linear regression to create a weight vector.

Logistic regression is becoming more popular as sophisticated statistical software for fast computers becomes more widely available. Due to this increased usage, readers, editors, and researchers must be aware of what to anticipate from articles that make use of logistic regression techniques. In educational research, particularly in higher education [20], logistic regression has become more prevalent [21]. A categorical outcome variable and one or more continuous or categorical predictor variables may be correlated, and this relationship can be expressed as a hypothesis and tested using the logistic regression method. Assume that a linear regression analysis only contains one continuous predictor (a child's reading score on a standardized test) and one dichotomous outcome variable (Y). The goodness-of-fit of logistic models was demonstrated by the R2 score, either for the entire model or for each predictor [22].

In one investigation, the findings were expressed as marginal probabilities [23]. Reference [24;25] have criticize the use of marginal probabilities because they don't correlate to a fixed change in the projected probabilities that will occur if one predictor (like reading) varies discretely while other predictors are realized at a constant. In other words, the marginal probability associated with a movement from 50 to 60 points is different than the marginal likelihood associated with a 10-point shift in reading from, say, 60 to 70 points.

Identifying the changes in stress states that occur when a structural part with residual stresses is subjected to a drilling operation is the basic tenet of the hole-drilling approach. There are many articles on this technique that give thorough explanations of the procedure [26-29]. The hole-drilling approach was employed at a metallurgical plant to ascertain the residual stresses in the case of the transverse beam supporting the casting ladle. A polynomial regression model has multiple power terms that follow one another. The highest order word as well as all other terms, important or not, will be included in each model. As a specific instance of multiple linear regression, polynomial regression can be viewed as such. For fitting curves, polynomial models provide a dependable and flexible technique. The regression analysis method that is most frequently used is ordinary least squares analysis. This technique involves the "best fit" line being drawn through all of the available data points, and parameter values are chosen to minimize the error sum of squares. To be fit, a regression model must adhere to a set of presumptions. To estimate the model's parameters, the errors must be taken to be uncorrelated random variables with a mean of zero and a constant variance. To perform hypothesis tests and interval estimates, the errors must have a regular distribution. Advanced statistical tests can be used to check the validity of these claims for a given regression equation.

1. **A look at statistical models in the future**

In this portion of the viewpoint on the future development of statistical models, appropriate solutions have been proposed for the four problems mentioned above.

(1). It is important to thoroughly examine the interpolation of meteorological data and statistical data for accuracy, and to compile thorough data on how climate change affects the agricultural sector. Using precise and thorough data, for instance, aids in comprehending how changes could be employed effectively. The data include phenology yield and management details at county and station scales, homogenization data of meteorological stations, accurate interpolators for weather data, continuous long-term crop growth, and other information. These thorough and precise SHI Review of statistical models for determining how the climate affects crop production. To investigate how the climate affects crop yields under various adaptations, 575 geographical data at different scales can be used. likewise, it makes sense to arrange data with similar characters together. In order to properly investigate how the climate influence crop yields, it is important to select the critical growth seasons for various crops.

(2). Crop yields should be eliminated as non-climatic trends, therefore distributions of yield data and climate data, such as hetero skedasticity of yield changes, spatial variations, etc., should be thoroughly taken into account. Future studies may employ higher order polynomials fitting, initial differences, or the addition of time variables to eliminate the effects of method advancements.

(3). Analyzing climate variables with minimal correlations among themselves can help to mitigate the consequences of the colinearity problem. To examine the influence of various weather conditions on crop growth and development during various growing seasons, agrometeorological station data on crop growth records is crucial. In order to reduce colinearity issues, it is critical to comprehend how agricultural yields react to climate variables. Combining crop models and statistical models to analyze yield responses to climate change can also overcome the colinearity problem.

(4). Researchers ought to categorize yield data according to different adaptations in an effort to address the problem of failing to take adaptations into account. This classification should be based on the collection of more specific information on management, weather, and yield. The yield responses to climate change should then be studied using time-series models, cross-section models, and panel models. Investigating how the climate impacts crop yields for different adaptations can be done very well by combining crop models.

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