

Analyzing Cost of Crop Production and Forecasting the Price of a Crop

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Abstract - Various technologies such as the Internet of Things, Artificial Intelligence, Drones, and others have been used to automate the agricultural sector in recent years. Because the weather is constantly changing, managing finances is a major concern in a country like India, and water is not always freely available, automation and precision are essential in this era. Researchers have come up with a slew of solutions, including weather forecasting, smart water management, inspecting crop quality, identifying disease, spraying pesticides on diseased crops, and so on. Machine learning, artificial intelligence, the internet of things, sensors, and other technologies are commonly used in these solutions. All of these solutions are intelligently managed and provide a high level of output and precision to assist a farmer in increasing productivity. Finance is the most important issue among these, yet it is not addressed by scholars. Only a few academics have used time series analysis to anticipate agricultural prices. And this predicting is limited to specific crops, vegetables, and fruits, as well as a specific region (s). There is no global mechanism for forecasting crop prices. We conducted a comprehensive evaluation of numerous strategies for predicting/forecasting agricultural prices, including various features, procedures/methodologies used, and their accuracy. We also provide research on the cost of crop production, why the cost of crop production is necessary, software available in the market for the purpose, formulae used in crop production calculations, elements considered in crop production calculations, and so on.

Key Words: AI, IoT, CNN, Crop production Cost, Crop Price Forecasting, Image processing.

1. INTRODUCTION

In reality, crop production costs are determined by a variety of elements, and if a digital platform offers such applications, accuracy is critical. After testing multiple strategies on a similar dataset, the accuracy of crop production cost prediction can be improved. As a result, the technique chosen is critical, as farmers' cost calculations cannot be as precise as those generated by an IoT-based system. Until far, scientists have focused their efforts on estimating the price of a certain crop. It has not yet been calculated using image processing and CNN. We propose a system that uses image processing or sensors to recognize various soil properties such as fertility, moisture, pH value, and so on, and then processes the data in the cloud to compute crop production costs.

2. Related Work

2.1 Predicting crop price

A lot of research has gone into forecasting the yield of a crop based on numerous factors such as weather, soil type, soil moisture, and so on. After that, a few scholars worked on predicting crop prices. The practice of forecasting crop prices (primarily) using time-series forecasting is known as crop price prediction. The majority of the academics focused on predicting/forecasting the price of a given crop. And the majority of them display results for their own country or region. Crop price forecasting at the global level has yet to be completed.

Prediction/forecasting of specific crop(s) price is critical not only for farmers (to yield specific crops for a specific region), but also for regional governments and other stakeholders such as supply chain marketers. Prediction/forecasting of specific crop(s) price is critical not only for farmers (to yield specific crops for a specific region), but also for regional governments and other stakeholders such as supply chain marketers. Tomato and maize (only for the state of Karnataka, India) [18], rabi and kharif [20], Arecanuts [21] (just for Kerala city of India), cabbage, bok choy, watermelon, and cauliflower [19] (for the capital of Taiwan, Taipei), tomato, onion, and potato (TOP crops, for India) [2]. Various models, such as univariate and multivariate models, have been proposed [1]. Exogenous variables such as VAR model [21], structured VAR model [22], ARIMAX, SARIMAX, and endogenous variables such as MA, ARMA, ARIMA [3] AND exogenous variables such as VAR model [21], structured VAR model [22], ARIMAX, SARIMAX. Researchers have proposed machine learning models such as support vector regression [4], LASSO [5], LSTM [6,7], ensemble models [20,24,25], and others.

[18] focuses on projecting tomato and maize prices in the Indian state of Karnataka. Trend analysis was employed as the methodology. Historical pricing, market arrival quantity of crops, historical weather data, and data quality-related factors were all utilized in this study. They concentrated on projecting agricultural prices while dealing with high price swings. They are more accurate than traditional forecasting techniques. [19] is concerned with forecasting cabbage, bok choy, watermelon, and cauliflower prices in Taiwan. The most important element in this work was the utilization of historical data to automate the forecasting procedure for the

crops indicated above. They employed four algorithms and created a new algorithm by combining two of them. The autoregressive integrated moving average (ARIMA), partial least square (PLS), and artificial neural network were the algorithms used (ANN). The PLS algorithm was combined with the response surface methodology (RSM) to create the RSMPLS algorithm. They propose PLS and ANN for short and long-term forecasting since they have low mistakes. The purpose of this [2] is to forecast monthly retail and wholesale prices of tomato, onion, and potato in India. They employed five multiplicative hybrid methods and two additive hybrid methods (Additive-ETS-SVM, Additive-ETS-LSTM) (Multiplicative-ETS-ANN, Multiplicative-ETSSVM, Multiplicative-ETS-LSTM, Multiplicative-ARIMA-SVM, Multiplicative-ARIMA-LSTM). The best results are obtained when mean absolute error (MAE), symmetric mean absolute percentage error (SMAPE), and root mean square error (RMSE) are used to anticipate tomato, onion, and potato prices.

The purpose of this paper [1] is to forecast the price of rabi and kharif crops such as paddy, arhar, bajra, and barley. Rainfall, temperature, market pricing, land area, and previous crop yields are all factors considered. They're also estimating the gain for the next year based on the previous year's statistics.

2.1.1 Dataset

Datasets are difficult to come by. The majority of the researchers used databases from government portals or organizations such as agricultural colleges, universities, and laboratories. For analysis, public repositories [1] are also employed. Researchers engaged departments such as the Horticultural Statistics Division, Department of Agriculture, Cooperation and Farmer Welfares, Govt. of India, and the Database of National Horticulture Board (NSB) [2] as study for specific crops progressed. Past data is important when anticipating price, so it was discovered that historical stock data [3] was utilized in stock market forecasting, and that technique assisted researchers in forecasting agricultural prices. A weather dataset from agmarknet [18] was used for weather prediction.

2.2 Calculating the cost of crop production

Farming is influenced by a variety of factors including weather, finances, manpower, labor, and others. Humans have no power over the weather. Manpower can be controlled or replaced in some way, and labor management can be done in the same way. Taking out loans or borrowing money from friends and family can also help manage finances. Repaying debts becomes difficult, however, if farmers do not generate the expected profit. Farmers can simply manage their finances if the cost of crop production can be calculated or estimated.

[10] Researchers worked on developing bioeconomic models to help farmers make better crop management decisions. In the late 1960s and early 1970s, several models were popular. They stated a number of models developed by researchers to estimate agricultural production costs depending on a variety of criteria. Anderson [11] modelled crop mix selection on an irrigated farm, Donaldson [12] modelled harvest machinery selection, and Flinn [13] modelled the crop irrigation system. It's a mathematical model for calculating profit-maximizing management techniques. [10] The focus was on four areas. Integration of bioeconomic models with crop record systems, enhanced interactive capabilities, model maintenance and transportability, and the separation of public and private sector roles. They also discussed prediction and process models, which function with tiny equations and clarify the connections between physical and biological processes. These models enable interactions between various stakeholders, allowing problems to be handled from several angles and production costs to be lowered.

[16] The focus is on numerous production alternatives. They also looked at soil water balance, nitrogen balance, and cereal development, among other things. Crop production analysis (mainly for impoverished farmers) is also done using various models and simulations. Many factors influence the cost of crop production, including improved seeds, chemical fertilizers, farm machinery, and large-scale irrigation with tubewells, which are referred to as modern inputs and are used instead of traditional inputs such as human labor, bullock labor, farm-grown seeds, manure, and so on [8]. The purpose of this paper [8] is to identify the origins of cost inflation and the role of various elements in the rising cost of crop farming. They employed ten crops from 19 key producing states across India (paddy, wheat, maize, and jowar from the cereals group, gramme and Arhar from the pulses group, rapeseed, mustard, and groundnut from the oilseeds group, and sugarcane and cotton among the other cash crops). The cost of cultivation is calculated using time series data from 1990-91 to 2014-15. They have demonstrated that modern inputs are the cause of rising cultivation costs, with increased crop prices, labor costs, and input costs as a result. The alternative is to not use any machinery or labor at all. The use of low-cost machinery may be a viable solution to this challenge.

Crop production costs rise as a result of the factors affecting cultivation costs. Researchers haven't concentrated on assessing the cost of production based on parameters such as soil fertility, moisture, pH level, hired assets, seeds fertilizers, pesticides, and so on. The production cost can be computed manually, with software, or with excel sheets. Rather, the farmer can forecast the cost of production, but he never checks the soil fertility, moisture content, or pH level so that he can invest wisely (as and when needed) and enhance his profit. Any program or freely available excel sheets do not take into consideration any of these criteria.

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As a result, the cost of crop production must be linked to the crop's profit. There must also be a good structure for cost calculations that takes into account all farming aspects and considerations. [10] The book focuses on calculating the cost of maize production in the United States and formulating the relevant factors. The cost structure is heavily influenced by fixed and variable costs, which can be added together to produce the total cost ($TC=FC+VC$). As the rate of planting increases, the profit decreases, hence it is not a viable option for lowering crop production costs. So, in order to lower crop production costs, one must first calculate them using excel sheet formats or online calculators, selecting the ideal quantity of inputs based on the needs of one's farm/land. Figure 1 depicts all of the variables taken into account when calculating agricultural production costs.

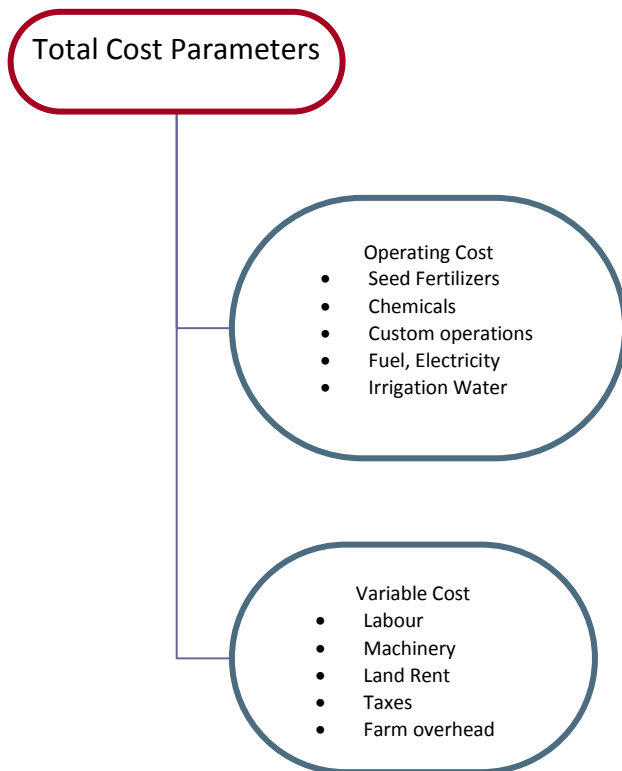


Fig -1: Total Cost Parameters

[9] Estimates the average cost of production for various crops in the Iowa region, such as corn, corn silage, soybeans, and so on. They investigate, calculate, and analyze the cost of production in relation to numerous characteristics as outlined in the book chapter [17]. If the product is made from other crops, the labor cost is termed a variable cost. They further claim that the cost of production varies from farm to farm due to variances in numerous characteristics. Examples of production costs for corn after maize, corn after soybean, corn after corn silage, and so on. Following Corn, Strip-Tillage Corn and Soybeans, Herbicide Tolerant

Soybeans Non-Herbicide Tolerant Soybeans Following Corn, Low-till Corn and Soybeans, Oats and Hay, Alfalfa-Grass Hay, and other examples are provided to estimate production costs, although actual costs may differ.

[14] Explains how precision agriculture influences production costs and how it may improve precision agriculture if best management techniques for crop production and environmental care are followed. [15] Calculates cost of production ranges and causes for annual and perennial energy crops in Europe.

3. CONCLUSIONS

Researchers have been working hard since the 1960s to develop models for less cost-effective agricultural production and higher revenues for farmers. These models are also used to determine things like irrigation system water management, nitrogen balance, and which machinery to utilize, among other things.

Using approaches like time-series forecasting to predict agricultural prices does not yield accurate results until and until more inputs from adjacent markets are considered. Farmers' ability to plan ahead of time and manage their cash and other resources is also hampered.

Farmers might readily anticipate their profit if they could assess production costs instead of forecasting crop prices. [23] [24] Calculations can be done with software and excel sheets, but they don't take into account variables like weather, land fertility, soil type, and so on. Farmers can forecast how much water is necessary for a given crop (whether it is grown in a rotational or non-rotational system), calculate soil fertility to help them invest wisely in fertilizers, and soil type to help them choose the crop to cultivate by considering these criteria.

Currently, researchers use IoT-based devices and machine learning algorithms to calculate each of these factors separately. Sensors are providing accurate results for soil fertility, soil moisture, pH levels, and other factors. They can be integrated with image processing to make them more automated, accurate, and cost-effective.

Farmers are now calculating all of these parameters using their own projections, which are not yielding great profits. These metrics may be estimated using smart technologies and machine learning algorithms, which would considerably help farmers manage their budgets and increase revenues.

REFERENCES

[1] Sadiq A Mulla and S. A. Quadri, "Crop-yield and Price Forecasting using Machine Learning", The International Journal of analytical and experimental modal analysis XII(Issue VIII, August/2020):1731-1737.

- [2] Sourav Kumar Purohit, Sibarama Panigrahi, Prabira Kumar Sethy, Santi Kumari Behera, "Time Series Forecasting of Price of Agricultural Products Using Hybrid Methods", *Applied Artificial Intelligence*, DOI: 10.1080/08839514.2021.1981659.
- [3] Ayodele Ariyo Adebisi, Aderemi Oluyinka Adewumi, and Charles Korede Ayo, "Comparison of ARIMA and artificial neural networks models for stock price prediction", *Journal of Applied Mathematics* 2014 (2014).
- [4] Kyoung-jae Kim, "Financial time series forecasting using support vector machines", *Neurocomputing*, Volume 55, Issues 1–2, September 2003, Pages 307–319.
- [5] Jiahua Li and Weiye Chen, "Forecasting macroeconomic time series: LASSO-based approaches and their forecast combinations with dynamic factor models", *International Journal of Forecasting* (2014).
- [6] Sima Siami-Namini and Akbar Siami Namin, "Forecasting economics and financial time series: ARIMA vs. LSTM", arXiv preprint arXiv:1803.06386 (2018).
- [7] Hansika Hewamalage, Christoph Bergmeir, and Kasun Bandara, "Recurrent neural networks for time series forecasting: Current status and future directions", *International Journal of Forecasting* 37, 1 (2021), 388–427.
- [8] S.K. Srivastava*, Ramesh Chand and Jaspal Singh, "Changing Crop Production Cost in India: Input Prices, Substitution and Technological Effects", *Agricultural Economics Research Review* Vol. 30 (Conference Number) 2017 pp 171-182 DOI: 10.5958/0974-0279.2017.00032.5.
- [9] Alejandro Plastina, "Estimated Costs of Crop Production in Iowa–2022", IOWA State University, extension & Outreach, Ag Decision Maker, FM 1712 Revised January 2022.
- [10] Caleb A. Oriade, Carl R. Dillon, Developments in biophysical and bioeconomic simulation of agricultural systems: a review, *Agricultural Economics*, 10.1111/j.1574-0862.1997.tb00463.x, 17, 1, (45-58), (1997).
- [11] Anderson, R.L. "A Simulation Program to Establish Optimum Crop Patterns on Irrigated Farms Based on Preseason Estimates of Water Supply." *American Journal of Agricultural Economics* 50(1968):1586-90.
- [12] Donaldson, G.F. "Allowing for Weather Risk in Assessing Harvest Machinery Selection." *American Journal of Agricultural Economics* 50(1968):24-4.
- [13] Flinn, J.C. "The Simulation of Crop-Irrigation Systems." *Systems Analysis in Agricultural Management*, ed. J.B. Dent and J.R. Anderson, pp. 123-151. Sidney: Wiley, 1971.
- [14] Schimmelpennig, D. (2018), "Crop Production Costs, Profits, And Ecosystem Stewardship With Precision Agriculture", *Journal Of Agricultural And Applied Economics*, 50(1), 81-103. Doi:10.1017/Aae.2017.23.
- [15] Karin Ericsson, Håkan Rosenqvist, Lars J. Nilsson, "Energy crop production costs in the EU", *Biomass and Bioenergy*, Volume 33, Issue 11, 2009, Pages 1577-1586, ISSN 0961-9534, <https://doi.org/10.1016/j.biombioe.2009.08.002>.
- [16] G.Y. Tsuji, G. Hoogenboom, P.K. Thornton, "Understanding Options for Agricultural Production", *Springer Science & Business Media*, 31-Jan-1998 - Science - 400 pages.
- [17] David E. Clay, Sharon A. Clay, Stephanie A. Bruggeman, "Cost of Crop Production", *Practical Mathematics for Precision Farming*, Jan 2017, Chapter 12.
- [18] Ayush Jain, Smit Marvaniya, Shantanu Godbole, Vitobha Munigala, "Towards Context-based Model Selection for Improved Crop Price Forecasting", 5th Joint International Conference on Data Science & Management of Data (9th ACM IKDD CODS and 27th COMAD) (CODS-COMAD 2022), January 8–10, 2022, Bangalore, India. ACM, New York, NY, USA, 9 pages, <https://doi.org/10.1145/3493700.3493725>.
- [19] Yung-Hsing Peng; Chin-Shun Hsu; Po-Chuang Huang, "Developing crop price forecasting service using open data from Taiwan markets", 2015 Conference on Technologies and Applications of Artificial Intelligence (TAAI), DOI: 10.1109/TAAI.2015.7407108.
- [20] Wen Shen, Vahan Babushkin, Zeyar Aung, and Wei Lee Woon, "An ensemble model for day-ahead electricity demand time series forecasting", 2013, Fourth International Conference on Future energy systems.
- [21] Kiran M. Sabu, T. K. Manoj Kumar, "Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala", Third International Conference on Computing and Network Communications (CoCoNet'19), *Procedia Computer Science* 171 (2020) 699–708.

[22] Huitong Qiu, Sheng Xu, Fang Han, Han Liu, and Brian Caffo, "Robust estimation of transition matrices in high dimensional heavy-tailed vector autoregressive processes", 2015, 32nd International Conference on Machine Learning, PMLR 37:1843-1851.

[23] <https://www.alberta.ca/crop-budget-calculator.aspx>.

[24] <https://extension.psu.edu/cost-of-production-calculator>.