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Applications of Statistical Methods in Agricultural Economics: A Review of Trends, Techniques, and Future Directions

***Gogulraj Murugesan Rajeswari*[*1,2] & K Rahul Aadithyan*[3]**

[1] *MOOD for Climate Action, Learning Planet Institute, Paris*

[2, 3] *School of Agricultural Sciences, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India*

***Corresponding Author Email:** rajrgogul@gmail.com

Abstract

Complex relationships between agricultural production, markets, policy, resource use and farm-level decision-making rely more and more on statistical methods needed to analyze agricultural economics. This review briefly summarises the prominent statistical tools used in agricultural economics and reviews their applications, the evolution and advancements of the methods and trends in statistical research. Descriptive statistics, regression analysis, time series models, index numbers, survey sampling techniques, and econometric models serve as means of solving production analysis, cost estimation, price forecasting problems, evaluating farm policies, and conducting farm research on surveys. It also summarizes the increasing applications of statistical software like R, STATA, SPSS and Python, which have helped in reproducible and data-driven agricultural research. In addition, the review examines the latest developments in machine learning, big data analysis, Bayesian statistics, and artificial intelligence and their applications to more effectively predict and make better decisions using traditional econometric modelling. The methodological problems currently faced, such as data quality and sampling bias, overreliance on the statistical significance and measurement error are also touched on. The review finds that future economic research in agriculture will increasingly be provided by hybrid analytical frameworks that are based on classical statistics together with computation, and are economically interpretable, transparent, and policy relevant. The synthesis aims to serve as a comprehensive, up-to-date overview for researchers, students, and policy makers in agricultural economics about the use of statistics and the ways it will develop in the future.

Keywords: *Econometrics; Big data; Artificial intelligence; Agricultural policy; R; Python.*

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Introduction to Agricultural Economics and Statistics:

Agricultural economics emerged as a very empirical field of economics and had early and important contributions to econometrics and continued focus on farm management, marketing, policy, trade and resource utilization (Runge, 2018; Cramer, 2018). This past history is also a reason why statistical thinking is not an add-on to the discipline but integral to its identity.

The subject now covers food systems, farm production, household choices, natural resources, natural resource management and policy assessment, and method(s) are needed that can describe variation, estimate relationships, test hypothesis and support prediction under uncertainty (Cramer, 2018; Mccalla et al., 2016). In reality, agricultural economists switch back and forth between descriptive summaries, regression, survey-based inference, time-series forecasting, index construction and even more data-intensive computational tools.

This review discusses some of the primary statistical techniques applied in agricultural economics, their aims and uses, and software environments in which they can be applied, as well as the changing methods which are influencing the discipline today. Another theme that is repeated in the literature is that methodological sophistication is important, but data quality, transparent interpretation and statistical versus economic significance are also important (Rommel & Weltin, 2020).

Role of Statistics in Agricultural Economic Research:

The link between theory and evidence in agricultural economics is operationalized by statistics. The field has a dependence on models to explain and predict production, consumption, prices, policy responses, and household behavior which are only useful when coupled with data and sound inference (Cramer, 2018; Mohamed, 2018). Within the realm of empirical research, statistical methods serve at least four purposes: description of farm and market conditions, estimation of production and cost relationships, assessment of the impact of policies, and forecasting for management or public decision-making purposes. There are a number of reasons for the growth of farm-level policy analysis, among them that policy tools are becoming more specific, analysts are now more interested in who is gaining or losing from policies than in averages alone, and better data and computing power make large-scale farm-level analysis possible (Heckelei, 2016).

There are also examples in the literature that statistics influences the quality of research. There were opportunities for improvements in reporting descriptive statistics, simulation and power calculations, and the interpretation of the significance of coefficients in economic and not only statistician sense in leading agricultural economics journals (Rommel & Weltin, 2020). As a reminder, both the choice of method and the method interpretation are pivotal to credible agricultural economic research.

Table 1: Core statistical roles in agricultural economics

Topic	*Main statistical role*	*Typical methods*
Farm and enterprise analysis	Describe heterogeneity and performance	Frequencies, ratios, PCA, clustering (Mangoejane & Christian,

		2025; Boiko et al., 2024; Huseynov et al., 2023)
Production and cost analysis	Estimate input-output relationships	Linear, Cobb-Douglas, quadratic, quantile regression (Qulmatova et al., 2022; Gautam, 2024; Amoozad-Khalili et al., 2020)
Prices and markets	Model dynamics and forecast volatility	ARIMA, SARIMA, VAR, hybrids (Zhao et al., 2024; Tenriawaru et al., 2023; Ray et al., 2023)
Policy evaluation	Identify impacts under non-random selection	DID, PSM, IV, panel models (Mojeed et al., 2025)
Survey-based measurement	Produce representative sector estimates	Stratified, multistage, dual-frame designs (Dubman, 2019; Bako et al., 2022; Ferraz et al., 2022)

Descriptive Statistics in Farm Management Studies:

Most farm management analysis begins with descriptive statistics, which provide an overview of farm structure, operator characteristics, input use, debt, output and regional differences before formal modelling is undertaken. When datasets combine household, farm business and production information, means, shares, dispersion measures and cross-tabulations are of particular importance.

Meanwhile, literature evidence indicates that the articles in agricultural economics journals tend to report mean values rather than provide a richer descriptive summary of the data, although it is important to provide a descriptive summary of the data for the interpretation of subsequent econometric analysis (Rommel & Weltin, 2020). This weakness is relevant in farm management activities where there is usually an economic dimension of heterogeneity in terms of farm size, enterprise type, region and household conditions.

Farm survey data supports the statement. In ARMS-based analysis of credit demand, differences between credit applicants and non-applicants were observed by operator age, commodity specialization, acres operated, location, and financial characteristics, with the contrast by farm size being the most pronounced (Ifft et al., 2018). In these situations, descriptive analysis is not just a summary of data, it is a discovery of patterns of segmentation that inform the specification of the model and interpretation of the policies.

Regression Analysis for Production and Cost Functions:

The significance of regression analysis in agricultural economics has been a long-standing feature and a primary tool for estimating production, cost and supply relationships. Historically, agricultural economists were pioneers in both the usage of the Cobb-Douglas regression and the development of a probability-based statistical framework in which to use the Cobb-Douglas regression, such as using individual-firm data and panel-style reasoning (Biddle, 2020; Biddle, 2020).

In production economics, regression techniques are used to estimate the reaction of production to inputs, technology, prices, risk, and environmental limitations. Reviews of the literature indicate that the literature has evolved beyond the traditional static approaches to a more comprehensive view that includes both structural and dynamic components of production, environmental impacts, risk, trade exposure and policy relevance (Carpentier et al., 2015; Tack et al., 2026).

While these models are still essential, there has been increased interest in the recent years in identifying models, model flexibility in terms of functional form, and the compromise between being well-founded and being well-estimated (Tack et al., 2026; Gardebrook & Kornelis, 2025). Regression is still the foundation for cost and production studies, but now it is playing field with and is interacting with more flexible predictive tools.

Table 2: Regression methods for production and cost analysis

Modeling task	***Reported methods***	***Main contribution***
Enterprise output response	Multiple linear regression	Links production to machinery and inputs (Qulmatova et al., 2022)
Production and cost functions	Cobb-Douglas, quadratic	Estimates elasticity, returns to scale, cost response (Marroquin, 2008; Amoozad-Khalili et al., 2020; Gautam, 2024)
Farm-level cost estimation	Random coefficient regression	Uses actual farm records even without commodity-specific accounting (Hornbaker et al., 2021)
Efficiency/frontier estimation	Regression quantiles, stochastic frontier	Produces robust efficiency scores and policy-relevant heterogeneity (Kaditi & Nitsi, 2019; Mangoejane & Christian, 2025)
Flexible nonparametric estimation	Additive spline-based models	Reduces MSE and bias versus DEA-style estimators (España et al., 2023)

Agricultural Prices and Forecasting – Time Series Analysis:

Time-series techniques play a crucial role in the study of prices, costs, inflation, cycles, and short-run forecasting, in particular, by agricultural economists. The seasonality, weather shocks, policy shifts and international connections are particularly sensitive characteristics of agricultural markets that require seasonality modeling for research and policy application.

Official data and farm accountancy data have been applied to agricultural cost predictions using exponential smoothing and Box-Jenkins ARIMA methods, which indicate that time-series analysis can assist short-term cost prediction and income estimation. In general, time-series methods are useful whenever analysts want to analyze market dynamics, predict price behavior, or develop forward-looking market indicators to make farm and policy decisions.

Recent reviews of related agricultural modelling studies also indicate a move towards more integrated modelling approaches that incorporate regression, time-series analysis and other models to support decision making under uncertainty of climate and production. The trend implies that time-series analysis will continue to be significant but more and more as part of a larger, hybrid system.

Index Numbers and Inflation in Agricultural Markets:

Index numbers have significance in agricultural economics because actual prices do not necessarily tell the complete story. Comparisons of prices over time, deflation of nominal prices, price summary across commodities, and trade and welfare analysis of policy distortions frequently require the use of price data.

Previous research on market distortions in agriculture has demonstrated that traditional measures of producer and consumer support are not necessarily good measures of economic impact, while scalar index numbers with a theoretical basis can better capture the trade- and welfare-destroying effects of price and trade measures. This conveys the impression that there is more than just descriptive book keeping in the index-number methods, and that they can be used to indicate substantive economic interpretation.

In general, index numbers are still relevant for the analysis of agricultural markets, as they can be used to adjust prices for inflation, to compare the terms of trade across markets, to monitor production costs, and to monitor policy developments. They are most useful if researchers are clear about weighting systems, the time periods used for comparison, and the economic interpretation of the index used in the reporting.

Econometric Models in Agricultural Policy Analysis:

Econometric modelling is a fundamental tool in the toolbox of the agricultural policy analyst because policy impacts can be mediated through behavioural responses and the fact that model behaviours can be heterogeneous between farms and that nonexperimental data can be used. Farm level policy analysis has increased in response to the increasing relevance of farm level instruments in the implementation of modern policies, and the growing availability of richer databases and computation abilities which, in turn, allows for more fine-grained simulations and estimation at this level (Heckelei, 2016).

Methodological reviews of agricultural production economics also indicate that models that consider dynamic adjustment, environmental externalities, risk, and market integration are rapidly coming to replace simple average treatment comparisons for policy evaluation (Carpentier et al., 2015; Tack et al., 2026). In some policies, estimating a coefficient is not enough; rather, the task is to choose an appropriate framework to model the decision problem and data at hand.

There are also a handful of new additions to the toolbox in the newer literature. Bayesian econometrics is emerging as a new area of interest as recent advances in computing power provide greater capacity to draw more robust inferences, to make better predictions and to model uncertainty flexibly in agricultural and resource economics. Concurrently, journal reviews highlight that at the same time, policy-oriented empirical studies often lack the necessary attention to economic importance, test power and robustness all of which are important in the context of actual policy decisions (Rommel & Weltin, 2020).

Table 3: Statistical methods for prices and inflation analysis

Market question	***Main methods***	***Reported use***
Crop price forecasting	ARIMA, SARIMA, smoothing	Seasonal crop-price prediction (Zhao et al., 2024; Jadhav et al., 2017)
Volatile price series	ARIMA-GARCH, ARIMA-LSTM	Better volatility handling and forecast accuracy (Ray et al., 2023)
Food inflation dynamics	VAR, IRF, cointegration tests	Dynamic CPI response to commodity shocks (Tenriawaru et al., 2023)
Commodity price indices	CPI, Laspeyres, FAO-style indices	Track food-price trends and cost-of-living pressure (Bai et al., 2021; Dinku, 2024; Ceylan et al., 2025)

Sampling Methods for Farm Surveys:
Sampling is a critical issue in agricultural economics because many aspects of agriculture rely heavily on farm surveys and not on controlled experiments. The design of the survey also dictates the samples of people being observed, the representativeness of the data, the magnitude of the measurement error, and the confidence one can have in the econometric estimates.

Agricultural data collection has recently been studied, with the focus on minimising measurement error and maximising coverage, and evidence that data structure influences the empirical models that can be credibly estimated (Carletto et al., 2021). This is especially critical in agriculture, where the seasonality of the survey, recall error, plot-level variation, and nonresponse can have significant impact on findings.

The general econometric advice for using survey data also continues to be very useful: adequate treatment of survey weights, clustering, heteroskedasticity, panel structures and repeated cross-sections is important for inference from farm surveys (Deaton, 2019). Concerns are evident in teaching priorities, such as a need for more attention to sampling error, data quality, and the design of the trade-off between larger samples and lower-noise measurement.

Statistical Software (R, STATA, SPSS, Python) in Agricultural Economics:

The method itself has been integrated with statistical software, as estimation, forecasting, simulation, cross validation and visualization are often key parts of modern agricultural economics and must be achieved in a reproducible way. Practical limits are now not only statistical theory, but also the implementation that is transparent and efficient.

New texts in agricultural statistics have recently given more attention to modern computer applications and the wider range of data types, as software environments now influence the decisions that are made regarding analysis in agricultural research. In actual practice, R and STATA are still popular choices for econometrics and applied statistics, SPSS continues to be used for teaching and survey use, and Python is becoming more appealing due to its popularity in machine learning, data engineering, and connecting with large or unstructured datasets.

The machine-learning literature in agricultural economics also highlights the need to lower upfront costs of implementing more sophisticated predictive approaches, such as through the use of free, open-source software, like Python and R (Ifft et al., 2018). Thus, software selection is shifting from a single tool to the right tool for the job, with STATA and R being used for classical econometrics, R and Python for reproducible data analysis, and Python particularly for machine-learning and large-scale data analysis.

Table 4: Software ecosystems used in agricultural statistics

Software	*Strengths*	*Typical use*
R / RStudio	Open source, flexible, spatial and experimental add-ons (Shimizu et al., 2025; Postiglione et al., 2021)	Econometrics, spatial analysis, reproducible workflows
SPSS	Easy training path for applied economists (Swinton & Labarta, 2019)	Survey analysis, hypothesis tests, linear and logit models
STATA	Strong interface and general statistical capability (Dubrovin et al., 2023)	Applied econometrics and reporting
Python	Flexible, scriptable, ML-ready (Dubrovin et al., 2023)	Automation, machine learning, custom analytics
AgroR / Assistat	Accessible agricultural analysis interfaces (Shimizu et al., 2025; De Assis Santos E Silva &	ANOVA, assumption checks, agricultural experiments

Azevedo, 2016)

Emerging Trends: Machine Learning, Big Data, and AI in Agricultural Economics:

One of the most evident changes in the methodology in the recent literature has been the increase in machine learning, big data and computational approaches. The use of machine learning to overcome the limitations of traditional econometric and simulation toolkits has been discussed in the context of agricultural economics, particularly when the researcher is constrained to adopt a functional form, to have a large number of explanatory variables, to have unstructured data, or to have a prediction task in which the accuracy of the result is more important than the interpretation of the coefficients (How Agricultural Economists Are Using Big Data: A Review - Emerald Insight, 2022 ; Storm et al., 2019).

There is some empirical evidence which gives reasons for limited optimism, not wholesale rejection of econometrics. The best performing machine-learning models in ARMS-based prediction of farm credit demand were superior to a literature-based logistic regression in their ability to recall and, in some cases, precision, but the superior model still depended on the goal of the decision-maker and the cost of false positive versus false negative results of the prediction (Ifft et al. 2018).

Big data reviews also highlight the use of public, private, and administrative data by agricultural economists, as well as problems with data management and privacy and the difficulty of combining theory-driven and data-driven approaches (How Agricultural Economists Are Using Big Data: A Review - Emerald Insight, 2022 Ifft et al., 2018). The most convincing recent analyses don't see AI as an alternative to economic thinking. Rather they advocate for integration and the adaptation of machine learning to causal analysis, policy evaluation and interpretable decision support (Gardebroek & Kornelis, 2025; Storm et al., 2019).

Challenges and Future Research Directions:

The difficulty that now faces the statistical worker in agricultural economics is not to have too many methods. It matches approaches to questions, data quality and decision context. These methodological issues – namely measurement error, coverage bias, uncritical significance testing, and weak attention to economic magnitude – have been identified as recurring challenges in reviews. These are recurring methodological problems that have been identified in reviews: measurement error, coverage bias, uncritical significance testing, and weak attention to economic magnitude (Carletto et al., 2021; Rommel & Weltin, 2020).

Research into the future will probably proceed in five directions:

- Machine learning will be most effective when used together with the economic structure, not as an automated replacement (Gardebroek & Kornelis, 2025; Storm et al., 2019).
- Rich data infrastructure: Explicitly more data about farms, markets, environmental conditions, and administration are required to enable computational agricultural science and policy analysis (Antle, 2019).

- Enhanced survey design and inference: Better research relating to measurement error, representativeness and weighting will lead to more reliable evidence at the farm level (Carletto et al., 2021; Deaton, 2019).
- Increased focus on economic significance – journals, reviewers, and teaching programs should ensure interpretation beyond p values (Rommel & Weltin, 2020).
- Hybrid modeling systems – future applications will likely involve the integration of econometrics, time series, simulation, spatial information, and AI, all within the same analytic system (Ramsey et al., 2025; Modi & Ketelo, 2026; Tack et al., 2026).

Conclusion

Statististical approaches have impacted the study of agriculture from its earliest beginnings and continue to be important in the study of farms, markets, households, and policy in agricultural economics. The discipline's traditional toolbox continues to include descriptive statistics, regression, time-series analysis, index numbers, survey sampling, and econometric modelling, and new tools such as Bayesian methods, machine learning, and big-data analysis are adding to the possibilities of questions and answers (Runge, 2018; Carpentier et al., 2015; Tack et al., 2026; Ramsey et al., 2025; Storm et al., 2019).

The path is obviously going to the left. Agricultural economics is data rich, computation rich, and pluralistically method rich. The best future research will not discard classical statistics, but rather incorporate the foundations of classical statistics with improved data, a better interpretation, and carefully integrated AI-based methods that are still economically meaningful and policy relevant (Gardebroek & Kornelis, 2025; Antle, 2019; Storm et al., 2019; Ifft et al., 2018)

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