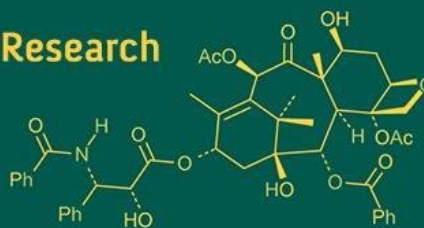


International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693
ISSN Online: 2617-4707
NAAS Rating (2026): 5.29
IJABR 2026; SP-10(4): 656-664
www.biochemjournal.com
Received: 16-01-2026
Accepted: 18-02-2026

Saloni Patil
Department of Agronomy,
School of Agriculture, Lovely
Professional University,
Phagwara, Punjab, India

Manzoor A. Khanday
Department of Statistics,
Lovely Professional
University, Punjab, India

Makey Sri Chakra Naga Vardhan
Department of Agronomy,
School of Agriculture, Lovely
Professional University,
Phagwara, Punjab, India

Bunga Enosh
Department of Agronomy,
School of Agriculture, Lovely
Professional University,
Phagwara, Punjab, India

Corresponding Author:
Saloni Patil
Department of Agronomy,
School of Agriculture, Lovely
Professional University,
Phagwara, Punjab, India

Design and Analysis of Agronomic Field Experiments: A Review

Saloni Patil, Manzoor A Khanday, Makey Sri Chakra Naga Vardhan and Bunga Enosh

DOI: <https://www.doi.org/10.33545/26174693.2026.v10.i4Sh.8178>

Abstract

Field experiments are essential in development of agricultural productivity, sustainability and efficiency of resource use. The soundness of the findings made out of such experiments greatly relies on the strength of the experimental design and the right kind of statistical analysis. This review critically analyses classical and contemporary methods of designing and analysing agronomic field trials, and in doing so, emphasizes issues like spatial heterogeneity, environmental variability and interference of treatments. Conventional designs (such as totally randomized design (CRD), randomized complete block design (RCBD), factorial arrangement, and split-plot design) are considered as well as more sophisticated designs (row-column format design, spatial statistical model design and mixed-model design). The review also discusses the latest innovations, such as the incorporation of precision agriculture tools, geospatial technologies, and machine learning methods into the planning of experiments and data analysis. Although there has been a great improvement, there are still gaps in the use of spatially explicit models, addressing the neighbour effects and standardization of analytical frameworks. The article presents new possibilities in agronomic experimentation to include the use of artificial intelligence and real-time data analytics. In general, the synthesis highlights the necessity of a paradigm shift to more adaptive, data-driven and computationally robust experimental systems to improve the quality, reproducibility and applicability of agronomic research findings.

Keywords: Agronomic Field Experiments, Experimental Design, Spatial Variability, Precision Agriculture, Machine Learning in Agriculture

Introduction

The foundation of agronomic field studies is empirical evidence on how to enhance crop productivity, input efficiency, and sustainability in various agro-ecological settings (Kool *et al.*, 2020) ^[37]. These trials are necessary to test the varieties of crops, fertilizer management, irrigation, and pest control methods in practice in the field (Tanaka, 2021) ^[72]. But in contrast to controlled laboratory experiments, the field experiment is subject to spatial and time variability which may cause a great impact on the results of the experiment (Willers *et al.*, 2004) ^[79].

Agronomic experiment design is the key to eventual validity and accuracy of the findings. Minimization of bias and quantification of experimental error are based on classical principles of experimental design, including randomization, replication, and local control. Randomized complete block design (RCBD) and factorial designs are examples of designs that have been extensively used because they are simple to implement and they can manage the variability in the field (Hoefer *et al.*, 2020) ^[31]. However, with growing complexity in agricultural systems due to climate variability, soil heterogeneity, and precision farming technologies, more complex and adaptable experimental models are required (Mourtzinis *et al.*, 2021) ^[55]. Besides design, selection of statistical analysis techniques also has a significant effect on the interpretation of experimental data. Analysis of variance (ANOVA) has been the primary tool of agronomic research, but it does not always have the ability to capture the spatial correlation and random effect in field circumstances (Argaw *et al.*, 2025; Darghan *et al.*, 2024) ^[6, 19]. More recent developments in statistical modeling, such as linear mixed models, spatial methods, and Bayesian methods, provide better abilities to address such complexities (Gamulin *et al.*, 2024) ^[24]. In spite of these changes, a range of challenges remain, such as the deficiency of the use of the latest analytical tools, insufficient attention

to treatment interference, and the standardized reporting practices (Lee, 2023) ^[43]. Thus, to inform the future research, it is crucial to critically and thoroughly assess both traditional and modern approaches.

Experimental Design principles.

Fundamental Principles

Agronomic field experiments are based on three main principles: randomization, replication, and local control to determine their reliability and validity (Tanaka, 2021) ^[72]. These were first formalized by Ronald A. Fisher and are the focus of experimental research in agriculture. Randomization is a treatment that is randomly distributed among the experimental units so that any treatment has an equal probability of being assigned to any plot. This will reduce selection bias and aid in getting unbiased estimates of treatment effects. Randomization is another reason that the statistical tests can be used as they provide the independence of experimental errors (Berger *et al.*, 2021) ^[9].

Replication

It is the repetition of treatments in more than one experimental unit. It enables estimating experimental error and enhances comparisons of treatments. This is especially essential in field experiments, where the natural variability may confound treatment effects (Filazzola & Cahill, 2021) ^[23].

Experimental error is reduced by local control, often by blocking, to clump similar experimental units together. Agronomic research traditionally involves blocking along established gradients (soil fertility, availability of moisture or topography) (Koutra *et al.*, 2023; Mathews and Crossa, 2022) ^[39, 52]. Local control increases the sensitivity of the experiment by taking into consideration the variability (Mathews and Crossa, 2022) ^[52]. Although these principles form the basis of knowledge, their implementation in various agricultural environments, particularly on-farm experimentation, poses special issues (Sileshi, 2023) ^[69]. In particular, due to the inherent variability of fields managed by farmers and logistical constraints, on-farm experiments require a strong experimental design capable of providing statistical validity despite these complications (Cho *et al.*, 2021) ^[17].

These principles combined constitute the foundation to develop effective and statistically valid experiments. They however, when put into practical use need to be adapted to field specific limitations and research purpose.

Types of Experimental Designs in Agronomy

Various experimental designs are used in agronomic field experiments to answer various research questions in the presence of different degrees of field heterogeneity (Almaraz *et al.*, 2022) ^[4]. The design selection is a major factor that determines the accuracy, validity, and interpretability of findings. Although classical designs have been in popular use, their weaknesses in the conditions of complex fields have prompted the creation of more sophisticated and versatile designs. Randomized complete block designs and split-plot designs are the most frequently used types of experimental designs in agricultural and biological research and enable the randomization of factors within a multi-factorial experiment (Carvalho *et al.*, 2022) ^[14].

Completely Randomized Design (CRD).

The simplest type of experimental design is the Completely Randomized Design (CRD) in which experimental units are

randomly assigned treatments. This type of design presupposes that all the experimental units are identical, which is why it is best applicable to controlled settings, e.g. greenhouses or laboratory conditions (Suza & Lamkey, 2023) ^[71]. Although CRD is simple and easy to apply, it has seldom been employed in field experiments because of its failure to consider the spatial variability (Usman *et al.*, 2024) ^[75]. The uncontrolled fluctuation in soil fertility, moisture, and microclimate in heterogeneous agricultural fields may result in a higher degree of error in experiments and decrease the sensitivity of treatment comparisons (Sileshi, 2023) ^[69].

Key Observation

CRD is frequently used inapplicable in field conditions where the variability is high which results in wrongful conclusions. It is only applicable in a very homogeneous set of conditions or initial experimentations (Carvalho *et al.*, 2022; Usman *et al.*, 2024) ^[14, 75].

Randomized Complete Block Design (RCBD)

Randomized Complete Block Design (RCBD) is the most popular design in agronomic studies because it is effective in managing field variability. The experimental area in this design is subdivided into blocks, which form a relatively homogeneous unit. Assigning all treatments at random is done in each block (Edmondson, 2020) ^[21].

Blocking is used to manage variability due to known gradients like soil fertility or slope. The design minimizes experimental error by treating similar conditions in the same block and improves precision (Mathews & Crossa, 2022) ^[52]. But RCBD cannot be used in situations where the number of treatments is large (large block sizes) when field variability is complicated and not unidirectional, when there are many sources of heterogeneity.

Critical Insight

RCBD though popular, might lack the ability to equip contemporary agronomic experiments where spatial variability is complicated. The over-reliance of the RCBD without testing field uniformity can lower the efficiency in the experiment.

Latin Square Design (LSD)

Latin Square Design is applied where there is variability on both sides e.g. along rows and columns. Every treatment is used once in a row and column, which allows manipulation of two sources of variation at the same time (Koutra *et al.*, 2023) ^[39]. The design is more effective compared to RCBD in case there are two gradients (Usman *et al.*, 2024) ^[75]. Nonetheless, it is very restrictive as treatments should be equal to the number of rows and columns (Trinca & Gilmour, 2024) ^[74]; the missing data may have a devastating impact on analysis; layout is complicated in large experiments (Koutra *et al.*, 2023) ^[39]. This has made it difficult to implement on a large scale in field trials with a large number of treatments because its square dimensions are rigidly enforced (Jha *et al.*, 2025) ^[32]. Moreover, the naturally complicated nature of controlling various environmental gradients simultaneously in one design tends to eliminate its potential application in real-life agricultural contexts (Cho *et al.*, 2021) ^[17].

Critical Insight

Although theoretically powerful, LSD has drawbacks, such as not being able to test for every combination of treatments

(Ahmad *et al.*, 2025; Kusumiyati *et al.*, 2023) ^[1, 40]. Factorial Designs

Factorial designs are considered designs that are able to examine two or more factors simultaneously and at various levels, which enables the researcher to not only examine the primary effects of each factor, but also the interaction effects (Andrade, 2024; Yamada *et al.*, 2023) ^[5]. These designs are useful especially in the need to comprehend complex agricultural systems where many factors affect crop performance, which allows a more in-depth evaluation of treatment combinations (Carvalho *et al.*, 2021) ^[15]. As an example, a factorial design would be quite appropriate in research on the impact of various types of fertilizers and irrigation regimes on the crop yield, as it would help determine whether the effects of a specific type of a particular fertilizer are affected by the irrigation regime (Yamada *et al.*, 2023) ^[81].

In agronomy, factorial experiments may be used to investigate:

- Fertilizer × irrigation interactions
- Variety × planting density interactions.

The key benefit of factorial design is that it allows getting as much information as possible out of one experiment (Sharma and Sharma, 2021) ^[68]. But the more factors and levels, the more complex and hard to manage the design (Haug *et al.*, 2021) ^[28].

Critical Insight

Interaction effects tend to be biologically important in agriculture, but are commonly ignored or misunderstood. The interaction of these factors requires proper design and analysis of factorial experiments so as to capture these interactions.

Split-Plot Design

Split-plot designs are employed when factors need more room as experimental units than others. In this design the main plots are attributed to a single factor. Another factor is added to the subplots of each main plot. This hierarchical design can be used to capture factors that cannot be applied to a small scale, such as tillage or irrigation, and can represent other factors, such as fertilizer rates or crop varieties, on a smaller scale (Salinas-Ruiz *et al.*, 2024) ^[66].

It is often applied when the factors vary in their ease of application, e.g., irrigation (main plot) and fertilizer (subplot) (Majeed & Abood, 2021) ^[51]. The design is beneficial in the case of the experiment when various factors require various sizes of plots because of logistical limitations or the treatment application character (Li *et al.*, 2023) ^[45]. The major advantage of a split-plot design is that it is more accurate in measuring those factors that are difficult to manipulate and also the more detailed treatments can be assessed (Chanda *et al.*, 2021) ^[16].

The design is useful and common in field applications, but it brings in other degrees of experimental error:

- Error of main plot (vaguer)
- Subplot error (more accurate)

Critical Insight

The most frequent error is the analysis of split-plot designs as simple factorials that result in incorrect conclusions (Carvalho *et al.*, 2022) ^[14]. To prevent inflated significance,

it is necessary to manipulate statistics properly (Carvalho *et al.*, 2022).

Table 1: Comparison of Experimental Designs in Agronomy

Design	Key Features	Advantages	Limitations	Suitable Conditions
CRD	Random allocation	Simple	No variability control	Uniform conditions
RCBD	Blocking	Reduces error	Limited for complex fields	Field trials
Latin Square	Row & column control	High precision	Rigid	Two gradients
Factorial	Multi-factor	Interaction study	Complex	Multi-factor studies
Split-plot	Hierarchical	Practical	Different errors	Large-scale trials
Row-Column	2D blocking	High precision	Complex	Heterogeneous fields
Incomplete Block	Partial treatments	Efficient	Advanced analysis	Many treatments

A comparative summary of commonly used experimental designs is presented in Table 1.

Advanced and Modern Designs

As agricultural systems become more complex, more complex experimental designs are becoming significant (Li *et al.*, 2023; Longis *et al.*, 2024) ^[45, 47].

(a) Row-Column Designs

These designs are two-way extensions of blocking and are applicable in very heterogeneous fields. They offer enhanced management of spatial variability as opposed to RCBD. They work especially well in the case of two-way stratification of experimental units needed to counter the influence of environmental gradients (Usman *et al.*, 2024) ^[75].

(b) Incomplete Block Designs

In large number of treatments, it is not practical to incorporate all the treatments in each block. Incomplete block designs enable subsets of treatments in blocks, which increases efficiency. This method maximizes the resources allocation by decreasing the block size without compromising the statistical power, especially in experiments with multiple treatment levels (Usman *et al.*, 2024) ^[75].

(c) On-Farm and Participatory Designs

Such designs are carried out under actual farming conditions and in most cases they have farmers taking part in such experiments. They increase the practical applicability of research results but create more variability (Toffolini and Jeuffroy, 2022) ^[73].

(d) Spatially Optimized Designs

Spatial information (e.g., GPS, GIS) is becoming part of modern experiments to maximize the plot layout and minimize error variance (Song *et al.*, 2022) ^[70].

Critical Insight

Advanced designs are more precise and flexible (Kim *et al.*, 2021) ^[36] yet need more statistical skills and computing software (Song *et al.*, 2022) ^[70]. They are still not widely adopted in developing regions because of the lack of technical capacity (Ruzzante *et al.*, 2021) ^[65]. 6. Experiments in Agronomic Fields have difficulties.

Challenges in Agronomic Field Experiments

Agronomic field experiments are complex in nature because of the dynamic and heterogeneous nature of agricultural environment. In contrast to controlled laboratory trials, field trials are subjected to various sources of variability that may affect the accuracy, precision and reproducibility of the results. These challenges are essential to comprehend and tackle to design strong experiments and guarantee sound interpretations (Sileshi, 2023) ^[69].

Spatial Variability

Spatial heterogeneity is one of the greatest problems in field experimentation. Farmlands are not usually homogeneous but differ in terms of their fertility, texture and structure,

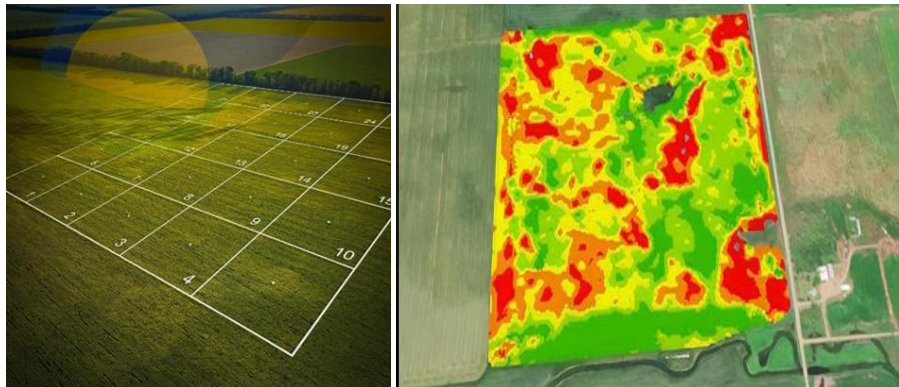


Fig 1: illustrates the extent of spatial variability typically observed in field conditions.

Temporal Variability

Temporal fluctuations such as rainfall variability, temperature, seasonal, Unexpected climatic events (Cabot *et al.*, 2023) ^[12] also affect agronomic experiments. These variables may have a great impact on crop growth and treatment performance especially in the rainfed systems. The change between years usually causes a lack of consistency in the results, and it is challenging to extrapolate the findings (Santosa *et al.*, 2024; Zhao *et al.*, 2025) ^[67, 85]. Critical Insight: The use of single-season experiments can lead to misleading conclusions (Pokovai *et al.*, 2024) ^[61]. The robustness and external validity of agronomic research requires multi-season and multi-location trials to enhance the research (Jones *et al.*, 2025) ^[33].

Treatment Interference (Neighbor Effects)

Treatment interference happens when a treatment has an effect on neighboring plots. It is especially prevalent in field experiments that include fertilizer treatments (nutrient transport), irrigation treatments (seepage of water), density or variety test of plants (competition effects) (Levin *et al.*, 2023) ^[44]. Neighbor effects do not assume treatment effects are independent and result in biased estimates of treatment effects (Aronow *et al.*, 2022; Kim, 2024) ^[7, 35]. Critical Insight: The vast majority of classical designs do not take into account the influences of interferences, which may lead to an over- or underestimation of the performance of the treatment (Wager & Xu, 2021) ^[78]. To alleviate this problem, it is necessary to include buffer zones or implement spatial models (Koutra *et al.*, 2023) ^[39].

Experimental Error and Uncontrolled Factors

Experimental error is the impact of uncontrolled and unknown sources of variability, such as pest and disease occurrences, Uneven management practices, Measurement errors, Human errors in field operations (DeKold and Robertson, 2023; Mathews and Crossa, 2022) ^[20, 52]. Such aspects lead to residual variability, which might mask treatment differences and diminish statistical power (Mathews & Crossa, 2022) ^[52]. Important Implication: Replication assists in determining experimental error, but it

moisture supply, the presence of organic matter (Zhuravleva, 2024) ^[86] and so on.

This variability may result in the differences in crop response that are not related to the tested treatments. It is hard to capture the intricate spatial patterns even with proper blocking (as in RCBD) when the variability is irregular or multidirectional (Jha *et al.*, 2025) ^[32].

Critical Insight

The traditional designs presuppose uniformity in blocks and this is not always realistic. Overlooking spatial variability may overinflate the error in the experiment and decline the capacity to identify the actual treatment effects (Mathews and Crossa, 2022; Tanaka, 2021) ^[52, 72].

does not remove it (Vogrin & Koten, 2024) ^[77]. Such errors should be reduced with better standardization of field work and data collection (Mahmoud *et al.*, 2022; Yang *et al.*, 2023) ^[50, 84].

Practical and Logistical Constraints

Practical limitations used to limit field experiments include

Limited land, Labor, Equipment, Time and budget constraints. These limitations impact the choices of plot size, treatments, and levels of replications. Experimental precision can also be impacted by compromises of logistical reasons in many cases (Jones *et al.*, 2021) ^[34]. Critical Insight: The statistical rigor can often be at odds with practical feasibility.

Data Complexity and Management Issues

Experiments in modern agronomy are producing more and larger data, with multi-factor experiments, Multi-location trials, Continuous data collected with sensors (Newman & Furbank, 2021) ^[58] all becoming increasingly common. Analysis and management of such datasets demand high statistical and computing capabilities, which are not always available to researchers (Brown *et al.*, 2020) ^[11]. Critical Insight: The disparity between the production of data and its analysis is increasing (Arribas-Bel *et al.*, 2021; Gillespie *et al.*, 2024) ^[8, 26]. In the absence of data management and analysis, information of value might be underutilized (Ezhilaras and Jaswanth, 2024).

Critical Insight

The gap between data generation and analytical capacity is widening (Arribas-Bel *et al.*, 2021; Gillespie *et al.*, 2024) ^[8, 26]. Without proper data management and analysis, valuable information may remain underutilized (Ezhilarasi & Jaswanth, 2024) ^[22].

Lack of Standardization and Reproducibility

One of the primary issues in agronomic studies is the absence of standard protocols in the design of experiments, Data analysis, Reporting of results (Hammond *et al.*, 2023) [27]. This creates problems with the comparison of studies and replication of results in different places and circumstances (Sileshi, 2023) [69]. Critical Insight: To increase the credibility and reproducibility of agronomic research, greater transparency and the use of standardized reporting frameworks are needed.

Statistical Analysis Methods in Agronomic Experiments

The correctness and meaning of agronomic field experiments greatly relies on the selection of the right statistical analysis techniques. Since field conditions are variable and complex in nature, statistical tools are important in isolating the effects of treatment and the background noise. The methods of analysis employed by agronomy have over time shifted to simplistic forms of classical analysis to complex and adaptable modeling frameworks (Mowers *et al.*, 2022) [56].

Table 2: Statistical Methods Comparison

Method	Use	Strength	Limitation
ANOVA	Basic analysis	Simple	No spatial handling
Mean tests	Comparison	Easy	Error risk
Mixed models	Complex data	Flexible	Skill needed
Spatial models	Field correction	Accurate	Complex
Bayesian	Uncertain data	Flexible	Intensive
ML methods	Prediction	Powerful	Less interpretable

Table 2 provides a comparative overview of statistical analysis methods used in agronomy.

Classical Methods: Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) has long been the main pillar of statistical analysis of agronomic experiments (Carvalho *et al.*, 2022) [14]. It is a commonly used test to determine the importance of treatment effects by decomposing the overall variability into treatment, block, and experimental error components (Yamamoto *et al.*, 2022) [82]. The approach is specific to research designs like CRD, RCBD, and factorial experiments (Varalakshmi, 2025) [76]. ANOVA is based on a number of assumptions, such as independence of observations, homogeneity of variance, and homogeneity of residual normality (Ledolter *et al.*, 2020) [42]. ANOVA offers a strong framework of hypothesis testing when these assumptions are met. After a significant F-test, various comparison methods, including Least Significant Difference (LSD) or Tukey test, are used to compare treatment means (Ledolter *et al.*, 2020). ANOVA is limited in a few ways, in spite of its popularity. It fails to appropriately represent spatial correlation or more complicated error structures traditionally found in field experiments. Additionally, its assumptions may be violated, which may also result in incorrect inferences, especially in heterogeneous environments (Hawinkel *et al.*, 2022) [29]. Despite its widespread use, ANOVA has notable limitations. It does not adequately account for spatial correlation or complex error structures commonly present in field experiments. Moreover, violations of its assumptions can lead to incorrect inferences, particularly in heterogeneous environments (Hawinkel *et al.*, 2022).

Mean Comparison Procedures

Mean comparison tests are frequently employed to determine certain differences among treatment levels

following identification of overall significance with ANOVA. LSD, Multiple Range Test (DMRT) by Duncan and Honest Significant Difference (HSD) by Tukey are common techniques used in agronomic studies (Carvalho *et al.*, 2022) [14]. Although these techniques are applicable in interpreting treatment effects, they are different in their ability to control Type I error rates. As an example, LSD is less conservative and can result in a higher number of false positives, but Tukey test is less liberal and can be used in case of multiple comparisons (Nanda *et al.*, 2021) [57]. The major drawback of these tests is that they rely on the validity of ANOVA assumptions (Bittner, 2022) [10]. Moreover, overinterpreting results may be caused by overreliance on pairwise comparisons in the absence of biological relevance (Lin and Peddada, 2023) [45, 46].

Linear Mixed Models (LMMs)

Linear Mixed Models are one of the major improvements in the agronomic research analysis. LMMs allow both fixed and random effects in comparison with classical ANOVA where all factors are fixed. The latter flexibility comes in handy especially when analyzing data of multi-location and multi-year experiments (Madden & Ojiambo, 2024) [49]. The location, year, and replication are usually taken as random effects in agronomic trials whereas treatments are usually considered as fixed. It will be more effective to estimate the effects of treatment and increase the generalizability of findings (Yan, 2021) [83]. The LMMs also offer a means of dealing with unbalanced data and missing observations, which are prevalent in field experiments (Hoarau *et al.*, 2021) [30]. Nevertheless, they involve more advanced statistical skills and computation resources to be used (Piepho *et al.*, 2022) [60].

Spatial Analysis Techniques

One of the primary sources of error in field experiments is spatial variability, which is not properly considered by traditional methods (Tanaka, 2021) [72]. Spatial analysis tools overcome this shortcoming by simulating the relationship between adjacent plots (Hawinkel *et al.*, 2022) [29]. These approaches involve the use of spatial covariance structures in the analysis, which can enable more accurate estimates of the treatment effects. They minimize residual error variance by modifying spatial trends, and maximize the efficiency of experiments (Hoefer *et al.*, 2020) [31]. Spatial models, although with these benefits, are not applied in regular agronomic studies (Roberts *et al.*, 2021) [64]. This is mostly because it is complicated to implement and not all researchers are aware of it (Roberts *et al.*, 2021; Song *et al.*, 2022) [70].

Bayesian Approaches

The Bayesian statistical techniques provide a different model of data analysis that takes into consideration the prior information and observed data. This method is especially applicable when there is limited data or when it is highly uncertain (Menin, 2024) [53]. To estimate the effects of treatments more flexibly, utilize expert knowledge, and manage complex hierarchical models, Bayesian approaches can be used in agronomic research (Gamulin *et al.*, 2024; Ramsey and Rejesus, 2021) [24, 62]. The most important benefit of Bayesian analysis is that it allows to give results probabilistic interpretations that can be more informative than standard p-values. Nonetheless, the method depends on

the proper choice of previous distributions and computing skills (Leadbetter *et al.*, 2024) ^[41].

Integration of Machine Learning Techniques

Recent developments in computational science have brought with them machine learning methods in agronomic data analysis. These should be able to process large and intricate datasets, including those created by precision agriculture technologies (Rane & Choudhary, 2023) ^[63]. Predictive modeling of crop performance, pattern recognition in spatial and temporal data, experimental design optimization can be performed with the help of machine learning methods (Mourtzinis *et al.*, 2021; Nykei *et al.*, 2021) ^[55, 59]. These techniques have strong analytical abilities, but they are frequently criticized due to being black-box and having no interpretability. As a consequence, it is necessary to integrate them with the conventional statistical procedures to both guarantee accuracy and transparency (Min *et al.*, 2024) ^[54].

Modern Innovations in Agronomic Experimental Design and Analysis

Recent developments in the agricultural research have seen the incorporation of new technologies and methods of analysis into the design and analysis of agronomic field experiments. The innovations will overcome the weaknesses of classical experimental designs, especially in the context of managing spatial variability, large data set and complicated interactions between factors (Alesso *et al.*, 2020) ^[2].

The introduction of precision agriculture technologies is one of the most influential phenomena because it allows site-specifically managing crops by using sensors and drones and satellite images. The tools enable the collection of data on soil properties, crop growth, and the environment at high-resolution data. This has led to a possibility of using spatially explicit information in experimental designs to enable researchers to optimise the plot layout and make better treatment comparisons (Alesso *et al.*, 2020) ^[2].

Geographic information systems (GIS) and global positioning systems (GPS) have also increased the potential to map and study variability in the field. Through the incorporation of geospatial data in the planning of experiments, scientists are able to construct experiments which are more representative of the heterogeneity of the underlying field. This has brought about the creation of spatially optimized designs, which enhance accuracy by matching experimental units with natural field gradients (Alesso *et al.*, 2020) ^[2].

The other significant innovation is the growing use of sensor-based and real-time data collection systems. The use of technologies like soil moisture sensors, weather stations, and remote sensing platforms, produces constant streams of data, which allows dynamic monitoring of the conditions of an experiment. This change in static to dynamic data collection enables a closer analysis of crop responses in time, enhancing the understanding of the effects of treatments (Kortbein *et al.*, 2026) ^[38].

Statistically, the combination of cutting-edge computational tools has greatly increased the ability of analysis. More complicated modeling techniques, such as linear mixed models, spatial analysis, and simulation-based ones, are now supported by software platforms. These tools enable the

researcher to flexibly and more accurately examine large and unbalanced datasets (Choudhary *et al.*, 2024) ^[18].

Agronomic research has also been changed further with the emergence of artificial intelligence (AI) and machine learning (ML). These methods are able to detect trends, infer results and make optimal designs of the experiment using massive data. To provide an example, the model of crop behavior in different conditions can be predicted using machine learning algorithms, thus supporting decision-making and planning of experiments in new conditions (Mourtzinis *et al.*, 2021) ^[55].

Also, there is an increasing interest in participatory and on-farm experimental methods, in which farmers play an active role in the design and implementation of experimental methods. These methods make the research findings more practical and foster the implementation of innovations (Alexandre *et al.*, 2023; Campbell *et al.*, 2023) ^[3, 13]. Yet, they also add in more variability, which requires stronger and more flexible analytical frameworks (Sileshi, 2023) ^[69]. The implementation of modern technologies and techniques is still unequal despite these developments. High cost, technical incompetence, and inadequate access to computational tools are some of the challenges that reduce their adoption in most parts, especially in the developing regions (López *et al.*, 2022) ^[48].

In summary, contemporary advances are transforming agronomic experimentation through the ability to be more accurate, data-driven, and adaptive in research methods. Nevertheless, their integration to be successful demands technological development, as well as capacity building and methodological standardization.

Conclusion

Field experiments are still a mainstay of agricultural research, as they offer a key understanding of crop behavior, resource regulation, and sustainable production techniques. The success of these experiments is based primarily on the strength of its design and the suitability of statistical analysis.

As discussed in this review, classical experimental designs like CRD, RCBD, factorial, and split-plot designs have been a critical part of advancing agronomic research, but may not be adequate to capture the complexity of contemporary agricultural systems. Issues like spatial heterogeneity, temporal variability and interference in the treatment require more complex and adaptable solutions.

Developments of statistical tools such as linear mixed models, spatial analysis tools, and Bayesian models have greatly enhanced the analysis of complex agronomic data. Moreover, the introduction of recent technologies, including precision agriculture tools, geospatial systems, and machine learning, has provided new opportunities to improve the precision and efficiency of the experiment.

Nevertheless, there is still an essential gap between the presence of sophisticated approaches to research and their practical implementation in agronomic studies (Gava *et al.*, 2025) ^[25]. The insufficient technical skills, training, and unified guidelines still remain limiting the proper application of these innovations (Hammond *et al.*, 2023; Xie, 2025) ^[27, 80].

To find solutions to these problems, the future studies should be directed at creating the unified experimental systems that would unite sound design principles and up-to-date analytical instruments. The focus of future research

should be on capacity building, interdisciplinary cooperation and creation of user friendly analytical platforms. Also, reproducibility, transparency, and standardization of reporting of the experiment should be more focused in the future research.

To sum up, the future of agronomic field testing is in the change of the traditional, stagnant methods towards dynamic, data-driven solutions taking advantage of the technological progress and computing power. The change is necessary to enhance the quality, relevance, and effectiveness of agricultural research to meet the changing world challenges.

References

- Ahmad F, Kusumiyati K, Soleh MA, Khan MR, Sundari RS. Microclimates growing and watering volumes influences the physiological traits of chili pepper cultivars in combating abiotic stress. *Sci Rep*. 2025;15(1).
- Alesso CA, Cipriotti PA, Bollero GA, Martín NF. Design of on-farm precision experiments to estimate site-specific crop responses. *Agron J*. 2020;113(2):1366.
- Alexandre C, Tresch L, Sarron J, Lavarenne J, Bringer G, Chaham HR, Bendahou H, Carmen S, Borianne P, Koffi JMK, Faye É. Creating shared value(s) from On-Farm Experimentation: ten key lessons learned from the development of the SoYield® digital solution in Africa. *Agron Sustain Dev*. 2023;43(3).
- Almaraz M, Bingham N, Holzer I, Geoghegan EK, Goertzen H, Sohng J, Houlton BZ. Methods for determining the CO₂ removal capacity of enhanced weathering in agronomic settings. *Front Clim*. 2022;4.
- Andrade C. Understanding Factorial Designs, Main Effects, and Interaction Effects: Simply Explained with a Worked Example. *Indian J Psychol Med*. 2024;46(2):175.
- Argaw T, Fenta BA, Zegeye H, Azmach G, Funga A. Multi-environment trials data analysis: linear mixed model-based approaches using spatial and factor analytic models. *Front Res Metrics Anal*. 2025;10:1472282.
- Aronow PM, Samii C, Wang Y. Design-Based Inference for Spatial Experiments under Unknown Interference. *arXiv*. 2022.
- Arribas-Bel D, Green M, Rowe F, Singleton A. Open data products-A framework for creating valuable analysis ready data. *J Geogr Syst*. 2021;23(4):497.
- Berger VW, Bour L, Carter K, Chipman J, Everett C, Heussen N, Hewitt C, Hilgers RD, Luo Y, Renteria J, Ryznik Y, Sverdllov O, Uschner D, Beckman RA, Beckman RA. A roadmap to using randomization in clinical trials. *BMC Med Res Methodol*. 2021;21(1):168.
- Bittner AC. Analysis-of-variance (ANOVA) Assumptions Review: Normality, Variance Equality, and Independence. 2022:28.
- Brown D, Bergh IV, Bruin S, Machida L, Etten J. Data synthesis for crop variety evaluation. A review. *Agron Sustain Dev*. 2020;40(4).
- Cabot MI, Lado J, Bautista I, Ribal J, Sanjuán N. On the relevance of site specificity and temporal variability in agricultural LCA: a case study on mandarin in North Uruguay. *Int J Life Cycle Assess*. 2023;28(11):1516.
- Campbell B, Meadu V, Loboguerrero AM, Nowak A, Rosenstock TS, Shilomboleni H, Zougmore RB, Läderach P, Born L, Shelton S, Broeze J, Pereira L, Cosgrove B, Huyer S, Koerner J, Thornton PK, Campbell B, Aggarwal P, Keating BA, Zeppenfeldt L. Transforming Food Systems Under Climate Change through Innovation. Cambridge University Press; 2023.
- Carvalho AMX, Mendes FQ, Borges PH, Kramer M. A brief review of the classic methods of experimental statistics. *Acta Sci Agron*. 2022;45.
- Carvalho LC, Gonçalves E, Silva JM, Costa JM. Potential Phenotyping Methodologies to Assess Inter- and Intra-variety Variability and to Select Grapevine Genotypes Tolerant to Abiotic Stress. *Front Plant Sci*. 2021;12.
- Chanda B, Bhowmik A, Jaggi S, Varghese E, Datta A, Varghese C, Saha ND, Bhatia A, Chakrabarti B. Minimal cost multifactor experiments for agricultural research involving hard-to-change factors. *Indian J Agric Sci*. 2021;91(7).
- Cho JB, Guinness J, Kharel TP, Maresma Á, Czymmek K, Aardt J, Ketterings QM. Proposed Method for Statistical Analysis of On-Farm Single Strip Treatment Trials. *Agronomy*. 2021;11(10):2042.
- Choudhary S, Singh VJ, Singh SK. A Study of New Approaches to Statistical Analysis of Research data. *J Sci Innov Nature Earth*. 2024;4(4):24.
- Darghan AE, S TL, González N, Moreno CAR, Ospina-Noreña JE. The effect of spatial lag on modeling geomatic covariates using analysis of variance. *Appl Geomatics*. 2024;16(3):779.
- DeKold J, Robertson DJ. Field Based Phenotyping for Stalk Lodging Resistance: Experimental Error Analysis. Research Square. 2023.
- Edmondson RN. Multi-level Block Designs for Comparative Experiments. *J Agric Biol Environ Stat*. 2020;25(4):500.
- Ezhilarasi T, Jaswanth M. A Study on Implementation of Power Bi Dashboards to Streamline Business Processes. *Int J Res Appl Sci Eng Technol*. 2024;12(7):1548.
- Filazzola A, Cahill JF. Replication in field ecology: Identifying challenges and proposing solutions. *Methods Ecol Evol*. 2021;12(10):1780.
- Gamulin N, Zorić M, Karagić Đ, Terzić S. Assessing green manure impact on wheat productivity through Bayesian analysis of yield monitor data. *Front Plant Sci*. 2024;15.
- Gava O, Sturiale S, Gallardo M, Guerrero DB, Büyüktaş D, Aslan GE, Laarif A, Bouslama T, Navarro A, Incrocci L, Bartolini F. Addressing needs for the diffusion of digital greenhouse farming. Insights from Living Labs in the Mediterranean basin. *Bio-Based Appl Econ*. 2025.
- Gillespie A, Glăveanu VP, Laurent CS. Pragmatism and Methodology. 2024.
- Hammond J, Pagella T, Etten J, Ghosh A, Wijk MT. Editorial: Agile data-oriented research tools to support smallholder farm system transformation. *Front Sustain Food Syst*. 2023;7.
- Haug B, Messmer M, Enjalbert J, Goldringer I, Forst E, Flutre T, Mary-Huard T, Hohmann P. Advances in Breeding for Mixed Cropping - Incomplete Factorials

- and the Producer/Associate Concept. *Front Plant Sci.* 2021;11.
29. Hawinkel S, Meyer SD, Maere S. Spatial Regression Models for Field Trials: A Comparative Study and New Ideas. *Front Plant Sci.* 2022;13.
 30. Hoarau JY, Dumont T, Wei X, Jackson PRS, D'Hont A. Applications of Quantitative Genetics and Statistical Analyses in Sugarcane Breeding. *Sugar Tech.* 2021;24(1):320.
 31. Hoefler R, González-Barrios P, Bhatta M, Nunes JAR, Berro I, Nalin RS, Borges A, Covarrubias E, Díaz-García L, Quincke M, Gutiérrez L. Do Spatial Designs Outperform Classic Experimental Designs? *J Agric Biol Environ Stat.* 2020;25(4):523.
 32. Jha S, Zhang Y, Krogmeier JV, Buckmaster DR. A Web-Based Application Leveraging Geospatial Information to Automate On-Farm Trial Design. *arXiv.* 2025.
 33. Jones DL, Cooledge EC, Chadwick DR. Is one year enough? A commentary on field experiment duration in agricultural research. *Agric Syst.* 2025;228:104393.
 34. Jones M, Harbur M, Moore KJ. Automating Uniformity Trials to Optimize Precision of Agronomic Field Trials. *Agronomy.* 2021;11(6):1254.
 35. Kim B. Estimating Spillover Effects in the Presence of Isolated Nodes. *arXiv.* 2024.
 36. Kim S, Kim DS, Magana-Ramirez C. Applications of statistical experimental designs to improve statistical inference in weed management. *PLoS ONE.* 2021;16(9).
 37. Kool H, Andersson J, Giller KE. Reproducibility and external validity of on-farm experimental research in Africa. *Exp Agric.* 2020;56(4):587.
 38. Kortbein SL, Bathke KJ, Luck JD, Puntel LA, Thompson LJ, Balboa GR. Active crop canopy sensors improve nitrogen use efficiency in dryland maize. *Front Agronomy.* 2026;7.
 39. Koutra V, Gilmour SG, Parker BM, Mead A. Design of Agricultural Field Experiments Accounting for both Complex Blocking Structures and Network Effects. *J Agric Biol Environ Stat.* 2023;28(3):526.
 40. Kusumiyati K, Ahmad F, Khan MR, Soleh MA, Sundari RS. Productivity of Cherry Tomato Cultivars as Influenced by Watering Capacities and Microclimate Control Designs. *Open Agric J.* 2023;17(1).
 41. Leadbetter R, Cáceres GG, Phatak A. Bayesian Hierarchical Modelling of Noisy Gamma Processes: Model Formulation, Identifiability, Model Fitting, and Extensions to Unit-to-Unit Variability. *arXiv.* 2024.
 42. Ledolter J, Gramlich OW, Kardon RH. Parametric Statistical Inference for Comparing Means and Variances. *Invest Ophthalmol Vis Sci.* 2020;61(8):25.
 43. Lee SY. Using Bayesian Statistics in Confirmatory Clinical Trials in the Regulatory Setting. *arXiv.* 2023.
 44. Levin K, Winkhart F, Hülsbergen K, Reents HJ, Auerswald K. Artefacts in Field Trial Research—Lateral Ammonia Fluxes Confound Fertiliser Plot Experiments. *Agriculture.* 2023;13(8):1617.
 45. Li X, Storkey J, Mead A, Shield I, Clark IM, Ostler R, Roberts B, Dobermann A. A new Rothamsted long-term field experiment for the twenty-first century: principles and practice. *Agron Sustain Dev.* 2023;43(5).
 46. Lin H, Peddada S. Multigroup analysis of compositions of microbiomes with covariate adjustments and repeated measures. *Nat Methods.* 2023;21(1):83.
 47. Longis S, Cadoux S, Cordoue ALT, Tauvel P, Estienne M, Onzon P, Lescourret F, Rouillon C, Aubertot J. Performance of innovative cropping systems diversified with oilseeds and protein crops: identification and resolution of methodological issues, using the Syppre experimental network as a case study. *OCL.* 2024;31:2.
 48. López DM, Rico-Olarte C, Blobel B, Hullin C. Challenges and solutions for transforming health ecosystems in low- and middle-income countries through artificial intelligence. *Front Med.* 2022;9:958097.
 49. Madden LV, Ojiambo PS. The value of generalized linear mixed models for data analysis in the plant sciences. *Front Hortic.* 2024;3.
 50. Mahmoud R, Hilgert N, Casadebaig P, Gaudio N. A Workflow for Processing Global Datasets: Application to Intercropping. *SSRN Electron J.* 2022.
 51. Majeed AW, Abood MR. EFFECT OF ADDITION OF ORGANIC FERTILIZER AND ROOTSTOCK IN LEMON TRANSPLANTS EXPOSED TO WATER STRESS. *Plant Arch.* 2021;21:1463.
 52. Mathews KL, Crossa J. Experimental Design for Plant Improvement. 2022:215.
 53. Menin B. Objective Model Selection in Physics: Exploring the Finite Information Quantity Approach. *J Appl Math Phys.* 2024;12(5):1848.
 54. Min J, Song X, Zheng S, King C, Deng X, Hong Y. Applied Statistics in the Era of Artificial Intelligence: A Review and Vision. *arXiv.* 2024.
 55. Mourtzinis S, Esker PD, Specht JE, Conley SP. Advancing agricultural research using machine learning algorithms. *Sci Rep.* 2021;11(1).
 56. Mowers RP, Bucciarelli B, Cao Y, Samac DA, Xu Z. Good Statistical Practices in Agronomy Using Categorical Data Analysis, with Alfalfa Examples Having Poisson and Binomial Underlying Distributions. *Crops.* 2022;2(2):154.
 57. Nanda A, Mohapatra BB, Mahapatra APK, Mahapatra APK, Mahapatra APK. Multiple comparison test by Tukey's honestly significant difference (HSD): Do the confident level control type I error. *Int J Stat Appl Math.* 2021;6(1):59.
 58. Newman S, Furbank RT. A multiple species, continent-wide, million-phenotype agronomic plant dataset. *Sci Data.* 2021;8(1):116.
 59. Nyéki A, Kerepesi C, Daróczy B, Benczúr AA, Milics G, Nagy J, Harsányi E, Kovács A, Neményi M. Application of spatio-temporal data in site-specific maize yield prediction with machine learning methods. *Precision Agric.* 2021;22(5):1397.
 60. Piepho H, Gabriel D, Hartung J, Büchse A, Grosse M, Kurz S, Laidig F, Michel V, Proctor I, Sedlmeier JE, Toppel K, Wittenburg D. One, two, three: portable sample size in agricultural research. *J Agric Sci.* 2022;160(6):459.
 61. Pokovai K, Piepho HP, Hartung J, Árendás T, Bonis PA, Sugár E, Hollós R, Fodor N. Climate change related lessons learned from a long-term field experiment with maize. *Research Square.* 2024.
 62. Ramsey AF, Rejesus RM. Bayesian Hierarchical Models for Measuring Varietal Improvement in

- Tobacco Yield and Quality. *J Agric Appl Econ*. 2021;53(4):563.
63. Rane NL, Choudhary S. REMOTE SENSING (RS), UAV/DRONES, AND MACHINE LEARNING (ML) AS POWERFUL TECHNIQUES FOR PRECISION AGRICULTURE: EFFECTIVE APPLICATIONS IN AGRICULTURE. *Int Res J Mod Eng Technol Sci*. 2023.
 64. Roberts DP, Short NM, Sill J, Lakshman DK, Hu X, Buser M. Precision agriculture and geospatial techniques for sustainable disease control. *Indian Phytopathol*. 2021;74(2):287.
 65. Ruzzante S, Labarta R, Bilton AM. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Dev*. 2021;146:105599.
 66. Salinas-Ruiz J, López OAM, Crossa J. Strip-Plot Design. 2024:225.
 67. Santosa YT, Kurniasih B, Alam T, Handayani S, Supriyanta S, Ansari A, Taryono T. Investigating the dynamics of upland rice (*Oryza sativa* L.) in rainfed agroecosystems: an in-depth analysis of yield gap and strategic exploration for enhanced production. *Front Sustain Food Syst*. 2024;8.
 68. Sharma MJ, Sharma S. Critical Evaluation into the practical utility of the Design of Experiments. *Eng Manag Prod Serv*. 2021;13(3):50.
 69. Sileshi GW. Analytic transparency is key for reproducibility of agricultural research. *CABI Agric Biosci*. 2023;4(1).
 70. Song X, Evans K, Bramley RG, Kumar S. Factors influencing intention to apply spatial approaches to on-farm experimentation: insights from the Australian winegrape sector. *Agron Sustain Dev*. 2022;42(5).
 71. Suza W, Lamkey K. Quantitative Methods for Plant Breeding. 2023.
 72. Tanaka T. Assessment of design and analysis frameworks for on-farm experimentation through a simulation study of wheat yield in Japan. *Precision Agric*. 2021;22(5):1601.
 73. Toffolini Q, Jeuffroy M. On-farm experimentation practices and associated farmer-researcher relationships: a systematic literature review. *Agron Sustain Dev*. 2022;42(6).
 74. Trinca LA, Gilmour SG. Response Surface Designs for Crossed and Nested Multi-Stratum Structures. *arXiv*. 2024.
 75. Usman S, Jayeoba JO, Ari M, Amana SM. Research Methodology: An Agricultural Perception. *DergiPark*. 2024.
 76. Varalakshmi G. Application of Analysis of Variance (ANOVA) in Biological Science Research. *J Exp Agric Int*. 2025;47(9):520.
 77. Vogrin M, Koten JW. RUM leads to noise: the significance of finding the sources of variability between experimental runs. *Synthese*. 2024;204(5).
 78. Wager S, Xu K. Experimenting in Equilibrium. *Manag Sci*. 2021;67(11):6694.
 79. Willers JL, Milliken GA, O'Hara CG, Jenkins JN. INFORMATION TECHNOLOGIES AND THE DESIGN AND ANALYSIS OF SITE-SPECIFIC EXPERIMENTS WITHIN COMMERCIAL COTTON FIELDS. *Conf Appl Stat Agric*. 2004.
 80. Xie C. The role of modern agricultural technologies in improving agricultural productivity and land use efficiency. *Front Plant Sci*. 2025;16.
 81. Yamada JT, Viana RSE, Santos RR, Carvalho CP, Almeida MG, Barros JGM, Sampaio NA. Use of factorial design with significant interaction and Tukey's Test in agricultural and environmental experiments. *Rev Gest Secretariado*. 2023;14(6):9815.
 82. Yamamoto ELM, Gonçalves MC, Davide LMC, Rossoni DF, Santos A. Spatial variability in evaluation experiments of corn genotypes in the state of Mato Grosso do Sul, Brazil. *Acta Sci Agron*. 2022;44.
 83. Yan W. Estimation of the Optimal Number of Replicates in Crop Variety Trials. *Front Plant Sci*. 2021;11.
 84. Yang F, Liu Z, Wang Y, Wang X, Zhang Q, Han Y, Zhao X, Pan S, Yang S, Wang S, Zhang Q, Qiu J, Wang K. A variety test platform for the standardization and data quality improvement of crop variety tests. *Front Plant Sci*. 2023;14.
 85. Zhao F, Zhang Q, Wang H, Zhang K. Year patterns of climate impact models' performance: Long-term simulation of rainfed spring wheat production using five crop models under various climate patterns. *Agric Water Manag*. 2025;318:109704.
 86. Zhuravleva L. The influence of spatial heterogeneity of the properties of agricultural fields on productivity. *BIO Web Conf*. 2024;93:3004