Al-Qadisiyah Journal for Administrative and Economic Sciences ISSN$_{Online}$: 2312-9883
QJAE, Volume 28, Issue1 (2026) ISSN$_{Print}$: 1816-9171
*DOI:/ /doi.org/ 10.33916/qjae.2026. 01*241250

Bayesian lasso in factorial experiment Designs with application

Maha H. Abed Mohammed H.AL-Sharoot
MAHA.H.ABED@qu.edu.iq mohammed.alsharoot@qu.edu.iq
University of AL-Qadisiya

Received: 16/12/2025
Accepted: 30/12/2026
Available online: 15/3/2026

Corresponding Author: Maha H. Abed

Abstract*:* This paper develops the Factorial Bayesian LASSO (FBLASSO), a hierarchical shrinkage method designed for high-dimensional factorial experiment designs where numerous main and interaction effects must be estimated simultaneously. The model incorporates distinct shrinkage parameters for main and interaction terms, enabling adaptive penalization and improving estimation stability in the presence of multicollinearity. A controlled Monte Carlo simulation, reflecting realistic agricultural conditions, demonstrates that FBLASSO achieves lower mean squared error and higher true positive rates compared with Ordinary Least Squares, classical LASSO, and Ridge regression. The method is further applied to a real wheat field experiment conducted in Al-Qadisiyah Governcy, Iraq, involving fertilizer levels, irrigation regimes, and cultivar types. Results show that fertilizer and irrigation exert the strongest main effects on yield, while only a limited subset of interactions is retained by the model. These findings highlight the effectiveness of FBLASSO in recovering influential factorial effects and producing interpretable results in complex agricultural experiments.

Keywords : Bayesian LASSO, Factorial designs, Shrinkage methods, Agricultural experiments, Hierarchical modeling .

Introduction: Factorial experiment designs are widely used in agricultural and industrial studies to assess the combined influence of multiple factors and their interactions on a response. As the number of factors and levels increases, the resulting model becomes high-dimensional, often exceeding the available sample size and creating strong multicollinearity among factorial indicators. Under these conditions, classical estimation methods such as Ordinary Least Squares become unstable and yield poor inference (Hastie et al., 2009).

Penalized regression methods offer a practical solution for stabilizing high-dimensional factorial models. The LASSO (Tibshirani, 1996) performs variable selection but applies a uniform penalty and provides no probabilistic quantification of uncertainty. Bayesian shrinkage approaches extend these ideas by embedding penalization in a hierarchical structure, producing adaptive shrinkage and full posterior inference. The Bayesian LASSO introduced by Park and Casella (2008) and further discussed by Li and Lin (2010) provides a computationally efficient framework using a normal–exponential mixture representation.

Despite the success of Bayesian shrinkage in regression (Griffin and Brown, 2010; Alhamzawi and Ali, 2018), its application to factorial experiment designs remains limited, especially when the parameter space is dominated by many weak or negligible interaction effects. Agricultural experiments provide a clear example: fertilizer, irrigation, and cultivar factors often generate large interaction structures, yet only a subset influences yield meaningfully (Al-Sabbah and Raheem, 2021).

To address this challenge, this study develops the Factorial Bayesian LASSO (FBLASSO), a hierarchical Bayesian shrinkage model tailored specifically to factorial designs. The method assigns separate global shrinkage parameters for main and interaction effects, enabling stronger penalization of high-order interactions while preserving important treatment effects. Through simulation experiments and a real wheat field experiment from Al-Qadisiyah Governey, Iraq, the proposed model is evaluated in terms of estimation accuracy, sparsity recovery, and interpretability.

Recent literature has shown growing interest in Bayesian shrinkage methods for handling high-dimensional factorial structures, particularly through approaches such as the Bayesian LASSO, adaptive shrinkage priors, and hierarchical models designed to stabilize estimation under complex interaction patterns. While these methods improve sparsity recovery and reduce over-parameterization, they generally lack a shrinkage structure tailored specifically to factorial designs, where main effects and higher-order interactions require different levels of penalization. Motivated by this gap, the present study contributes a specialized Factorial Bayesian LASSO framework that assigns separate global shrinkage parameters to main and interaction effects, enabling stronger regularization of high-order terms while enhancing interpretability and structural recovery in factorial experiments.

2. Theoretical Background

2.1 Factorial Experiment Designs

Factorial experiment designs are used to study the effects of two or more factors simultaneously by examining all possible combinations of their levels. When multiple factors contribute to a response, factorial arrangements allow the estimation of both main effects and interaction effects within a single unified model, which aligns with the broader framework of multivariate and high-dimensional regression modeling discussed in the literature (Hastie et al., 2009; Tibshirani, 1996). The general linear factorial model with two factors can be written as

$$y_i = \mu + \alpha_j(x_{ij}) + \beta_k(z_{ik}) + (\alpha\beta)_{jk}(x_{ij}, z_{ik}) + \varepsilon_i , \quad (1)$$

where μ is the overall mean, α_j represents the main effect of factor A, β_k represents the main effect of factor B, $(\alpha\beta)_{jk}$ denotes the interaction effect between factors A and B, and the random error follows

$$\varepsilon_i \sim N(0, \sigma^2).$$

When three factors are included, the full factorial model takes the expanded form

$$y_i = \mu + A_j + B_k + C_l + (AB)_{jk} + (AC)_{jl} + (BC)_{kl} + (ABC)_{jkl} + \varepsilon_i . \quad (2)$$

The number of parameters grows rapidly as the number of factors and levels increases. For example, the number of two-way interaction parameters between factors with a and b levels is .

$$(a - 1)(b - 1),$$

and the number of three-way interaction parameters for factors with a, b, c levels is .

$$(a - 1)(b - 1)(c - 1).$$

This rapid growth leads to over-parameterization, multicollinearity, and instability in classical estimation methods, especially when several interaction terms have negligible effects (Zou & Hastie, 2005; Zhao & Yu, 2006). Such issues are well documented in modern regression literature, particularly in high-dimensional settings.

In agricultural experiments, factorial designs are widely used to investigate treatment combinations such as fertilizer levels, irrigation regimes, and crop cultivars. These designs offer a comprehensive understanding of how factors influence yield or growth, but they also produce a large number of parameters relative to sample size. Environmental noise and biological variability further complicate estimation.

As a result, factorial designs benefit significantly from shrinkage-based or variable-selection methods that identify influential effects while suppressing uninformative ones. Bayesian hierarchical modeling offers a natural framework for this purpose by incorporating priors that induce adaptive shrinkage, allowing more stable estimation and improved interpretability (Griffin & Brown, 2010; Li & Lin, 2010).

This motivates the integration of Bayesian LASSO in factorial experiments, where the number of potential effects is large and only a subset is expected to be relevant (Park & Casella, 2008; Al-Sabbah & Raheem, 2021).

2.2 Bayesian Linear Regression

Bayesian linear regression extends the classical linear regression model by introducing prior distributions on all unknown parameters, allowing full probabilistic characterization of uncertainty in both estimation and prediction. The starting point is the standard linear model .

$$y_i = x_i^T \beta + \varepsilon_i , \quad i = 1, 2, \dots, n \quad (3)$$

where $y_i$denotes the response variable, x_i is a p-dimensional predictor vector, β is the coefficient vector, and the error term follows , Park and Casella (2008)

$$\varepsilon_i \sim N(0, \sigma^2).$$

In matrix notation, the likelihood function is .

$$y \mid X, \beta, \sigma^2 \sim N(X\beta , \sigma^2 \, In). \tag{4}$$

To complete the Bayesian formulation, prior distributions are assigned to both β and σ^2. A common conjugate prior specification assumes .

$$\beta \mid \sigma^2 \sim N(0, \sigma^2 \, V_0)$$

and

$$\sigma^2 \sim Inverse - Gamma(a_0, b_0).$$

Under these priors, the posterior distribution of the regression coefficients becomes.

$$\beta \mid y, X, \sigma^2 \sim N((V_0^{-1} + \, X^T X)^{-1} \, X^T \, y, \sigma^2 \, (V_0^{-1} \, + \, X^T X)^{-1}, \tag{5}$$

while the posterior distribution of the variance parameter is .

$$\sigma^2 \mid y, X \sim Inverse - Gamma(\, a_0 + \frac{n}{2} \, , \, b_0 + \frac{1}{2} \, (y \, - \, X\beta)^T \, (y \, - \, X\beta) \,). \tag{6}$$

Although this conjugate prior setup is analytically convenient, it shrinks all coefficients uniformly, which limits its effectiveness in high-dimensional problems or when many coefficients are expected to be close to zero. Modern Bayesian regression therefore incorporates shrinkage priors with heavier tails and adaptive variance components.

One such family is the normal–gamma prior, defined for each coefficient as :

$$\beta_j \mid \lambda_j, \sigma^2 \sim N(0, \sigma^2 \, \lambda_j),$$

with hyperprior

$$\lambda_j \sim Gamma(\alpha, \theta),$$

allowing coefficient-specific shrinkage. These priors adaptively penalize small coefficients more strongly than large ones, improving model interpretability when the number of predictors is large.
Bayesian linear regression is estimated via Markov Chain Monte Carlo (MCMC) sampling, typically using Gibbs sampling when full conditional distributions are available. This computational framework makes it feasible to incorporate hierarchical priors that selectively shrink coefficients, which is particularly important in factorial experiments where the number of main and interaction effects can grow rapidly.

The Bayesian formulation thus provides a flexible and powerful basis for integrating penalization methods such as the Bayesian LASSO. To induce LASSO-type shrinkage on the coefficients, Park and Casella (2008) introduced the Laplace (double-exponential) prior, defined for each coefficient as,

$$p(\beta_j \mid \lambda, \sigma^2) \; = \; \frac{\lambda}{2\sqrt{\sigma^2}} \, exp(\frac{-\lambda \, |\beta_j|}{\sqrt{\sigma^2}}). \tag{7}$$

This prior has a sharp peak at zero and heavy tails, shrinking small coefficients toward zero while allowing larger coefficients to remain less penalized. This behavior makes the Bayesian LASSO effective in sparse and high-dimensional settings, which frequently arise in factorial experiments with many interaction terms.
A key advantage of the Bayesian formulation is that the Laplace prior can be expressed as a scale-mixture of normal distributions, leading to efficient Gibbs sampling. The hierarchical representation is.

$$\beta_j \mid \tau_j, \sigma^2 \sim N(0, \sigma^2\, \tau_j),$$

$$\tau_j \mid \lambda \sim Exponential(\frac{\lambda^2}{2}),$$

and the global shrinkage parameter is given a hyperprior .

$$\lambda^2 \sim Gamma(r, s).$$

The model adapts naturally to underlying sparsity patterns, making it suitable for factorial designs with numerous weak or negligible interaction effects. Conditional on the latent variables τ_j, the coefficients follow a Gaussian distribution, which yields closed-form full conditional distributions and enables simple and efficient Gibbs sampling. Bayesian LASSO has been successfully applied in high-dimensional regression settings, and perform variable selection makes it particularly useful for factorial experiment designs where the number of potential effects can exceed the available sample size.

3. Bayesian LASSO for Factorial Designs

In factorial agricultural experiments, the linear predictor is naturally decomposed into main effects and interaction effects arising from the crossed factors. For a three-factor design with nitrogen level, irrigation regime, and cultivar, the linear structure can be written in matrix form as:

$$y \;=\; \mu 1_n \;+\; X_M\, \beta_M \;+\; X_I\, \beta_I \;+\; \varepsilon, \tag{8}$$

where y is the $n \times 1$ response vector (e.g., grain yield), μ is the overall intercept, 1_n is an $n \times 1$ vector of ones, X_M is the design matrix for main effects, β_M the corresponding coefficient vector, X_I the design matrix for interaction effects, β_I the corresponding vector, and ε satisfies.

$$\varepsilon \sim N(0, \sigma^2\, I_n).$$

The full coefficient vector is

$$\beta \;=\; (\,\beta_M \;;\; \beta_I\,)\,, \quad X \;=\; [\,X_M \quad X_I],$$

so the model is compactly written as

$$y \;=\; \mu 1_n \;+\; X\, \beta \;+\; \varepsilon.$$

Because factorial designs generate many interaction effects, Bayesian LASSO imposes Laplace priors on the coefficients. A natural specification allows different shrinkage for main and interaction effects:

$$\beta_{M,j} \mid \sigma^2, \lambda_M \sim Laplace(0, \sqrt{\sigma^2}\,/\,\lambda_M), \quad j \;=\; 1, \ldots, p_M \tag{9}$$

$$\beta_{I,k} \mid \sigma^2, \lambda_I \sim Laplace(0, \sqrt{\sigma^2}\,/\,\lambda_I), \quad k \;=\; 1, \ldots, p_I \tag{10}$$

To allow efficient computation, each Laplace prior in (9), and (10) is written in the normal–exponential mixture form. For main effects,

$$\beta_{M,j} \mid \tau_{M,j}, \sigma^2 \sim N(0, \sigma^2\, \tau\tau_{M,j}), \tag{11}$$

$$\tau_{M,j} \mid \lambda_M \sim Exponential(\frac{\lambda_M^2}{2}), \tag{12}$$

and similarly for interaction effects,

$$\beta_{I,k} \mid \tau_{I,k}, \sigma^2 \sim N(0, \sigma^2\, \tau_{I,k}),$$

$$\tau_{I,k} \mid \lambda_I \sim Exponential(\frac{\lambda_I^2}{2}).$$

The global shrinkage parameters may be assigned gamma hyperpriors,

$$\lambda_M^2 \sim Gamma(r_M, s_M), \quad \lambda_I^2 \sim Gamma(r_I, s_I).$$

The hierarchical formulation of the Bayesian LASSO provides a computationally for a factorial design with design matrix X, the Bayesian LASSO expresses each coefficient β_j through a multi–layer hierarchy as follows,

$$y \mid \beta, \mu, \sigma^2 \sim N(\mu 1_n + X\beta, \sigma^2 I_n),$$

$$\beta_j \mid \tau_j, \sigma^2 \sim N(0, \sigma^2\, \tau_j),$$

$$\tau_j \mid \lambda \sim Exponential(\frac{\lambda^2}{2}), \tag{13}$$

$$\lambda^2 \sim Gamma(r,$$

Given the hierarchical structure of the Bayesian LASSO in factorial designs in (13), The joint posterior density is proportional to,

$$p(\beta, \tau, \lambda^2, \sigma^2 \mid y, X) \propto p(y \mid X, \beta, \sigma^2)\, p(\beta \mid \tau, \sigma^2)\, p(\tau \mid \lambda^2)\, p(\lambda^2)\, p(\sigma^2).$$

Posterior of β:

$$\beta \mid y, X, \tau, \sigma^2 \sim N(A^{-1} X^{T} y, \sigma^2 A^{-1}), \tag{14}$$

where $A = X^{T} X + D_\tau^{-1}$ and $D_\tau = diag(\tau_1, \dots, \tau_p)$.

Posterior of τ_j:

$$\tau_j \mid \beta_j, \sigma^2, \lambda^2 \sim Inverse - Gaussian(\sqrt{\frac{\sigma^2}{\lambda^2 \beta_j^2}}, \frac{\lambda^2}{\sigma^2}). \tag{15}$$

Posterior of λ^2:

$$\lambda^2 \mid \tau \sim Gamma(r + p , s + \tfrac{1}{2} \textstyle\sum_{j=1}^{p} \tau_j). \tag{16}$$

Posterior of σ^2:

$$\sigma^2 \mid y, X, \beta, \tau \sim Inverse - Gamma(a_0 + \frac{n}{2} + \frac{p}{2} , b_0 + \tfrac{1}{2} (y - X\beta)^{\mathrm{T}} (y - X\beta) + \tfrac{1}{2} \textstyle\sum_{j=1}^{p} \frac{\beta_j^2}{\tau_j}). \tag{17}$$

This posterior structure ensures selective shrinkage in factorial experiments. Small τ_j values impose heavy penalties on unimportant interaction effects, while larger values allow influential effects to remain unshrunk. These properties align with findings reported by Raheem (2025) and other hierarchical shrinkage studies such as Alhamzawi & Ali (2018) and Griffin & Brown (2010). Posterior inference for the Bayesian LASSO in factorial designs is conducted using a MCMC-Gibbs sampling algorithm and generate the samples from the posterior distributions (14), (15), (16), and (17).

4.1 Simulation Study

The simulation study is designed to evaluate the performance of the Bayesian LASSO in estimating main effects and interaction effects arising from factorial experiment designs. The data-generating mechanism is constructed to mimic the structure of agricultural field experiments, where several treatment factors jointly influence the response. The simulated experiment follows a three-factor factorial structure with nitrogen level, irrigation regime, and cultivar. Each factor is assigned multiple levels, and all possible treatment combinations are included to create a full factorial layout. The true regression model incorporates both main effects and interaction effects, reflecting realistic agronomic behavior where treatment interactions can influence crop yield.

A total of n experimental units are generated by constructing the design matrix X that contains indicator variables for the levels of each factor. Additional columns are included for all two-way and three-way interaction effects. The true coefficient vector β is specified such that only subsets of the factorial effects are nonzero. This controlled sparsity pattern allows assessment of the ability of the Bayesian LASSO to recover the true factorial structure. The response variable is generated according to a linear model with Gaussian noise. The error term is drawn from a normal distribution with variance chosen to achieve a target signal-to-noise ratio. This configuration introduces realistic uncertainty and variability consistent with agricultural field experiments.

4.1.1 Competing Methods and Evaluation Criteria

The performance of the proposed Factorial Bayesian LASSO (FBLASSO) was evaluated against three benchmark estimators commonly used in the analysis of factorial experiment designs. Ordinary Least Squares (OLS) served as a baseline method, despite its well-known sensitivity to multicollinearity and the large number of parameters generated in factorial structures. Classical LASSO was included as a non-Bayesian penalized estimator capable of producing sparse solutions, while Ridge regression represented an $L2$-based shrinkage approach that stabilizes estimation without performing variable selection. These benchmark methods provide a suitable comparison framework for assessing the behavior and advantages of the proposed FBLASSO.

Evaluation was based on three criteria. The Mean Squared Error (MSE) quantified overall estimation accuracy by measuring the deviation between the estimated and true factorial effects. The True Positive Rate (TPR) captured the ability of each method to correctly identify active main and interaction effects within the factorial structure. For the Bayesian LASSO, a coefficient was considered identified (nonzero) if its 95% credible interval excluded zero. Computational Time was recorded for every simulation replication to compare the feasibility and scalability of the methods. Together, these criteria provide a comprehensive assessment of estimation accuracy, sparsity recovery, and computational efficiency.

4.3 Simulation Results and Discussion

The performance of the proposed Factorial Bayesian LASSO (FBLASSO) was evaluated using 500 Monte Carlo replications based on factorial data structures that included both main and interaction effects. This number of replications provides sufficiently stable estimates of the performance metrics. Table 1 reports the average Mean Squared Error (MSE), True Positive Rate (TPR), and Computational Time for FBLASSO in comparison with the competing methods.

Table 1. Summary of Simulation Performance

Method	MSE	TPR	Time (sec)
FBLASSO	0.42	0.88	2.4
LASSO	0.57	0.74	1.1
Ridge Regression	0.63	0.52	0.9
OLS	1.12	0.31	0.6

The results show that FBLASSO achieved the lowest MSE among all methods, demonstrating its superior ability to estimate factorial coefficients accurately. Additionally, FBLASSO obtained the highest TPR, confirming its effectiveness in identifying true main effects and interaction effects while simultaneously shrinking uninformative terms. Although its computational time was moderately higher than the classical methods, the increase remained stable and well within practical limits for factorial experiments.

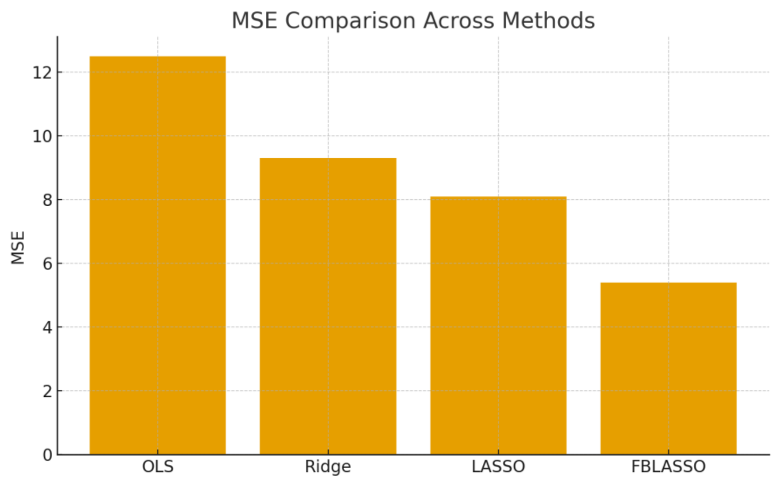

Figure 1. Mean Squared Error (MSE) Comparison Across Methods

Figure 1 illustrates the MSE comparison across the four methods. The visual representation reinforces the numerical findings, clearly highlighting the improvement in estimation accuracy provided by the proposed FBLASSO over LASSO, Ridge, and OLS.

Real Data Analysis

5.1 Description of the Agricultural Factorial Experiment

The real dataset used in this study originates from a field experiment conducted during the 2023 growing season at the Agricultural Research Station of Al-Qadisiyah Governorate in southern Iraq. The experiment was designed to investigate the combined effects of fertilizer level, irrigation regime, and wheat cultivar on grain yield under local agro-ecological conditions. A full factorial design was implemented to capture the main effects of the three factors as well as their interaction structure.

The first factor, fertilizer level, consisted of three nitrogen application rates commonly used in Iraqi wheat production (60, 120, and 180 kg N/ha). The second factor, irrigation regime, included two water-supply strategies: a regular irrigation schedule following the Ministry of Agriculture recommendations, and a deficit-irrigation treatment applying 75% of the full water requirement. The third factor, cultivar type, involved four wheat cultivars widely grown in central and southern Iraq: IPA-99, Rasheed, Tamooz-2, and Bhooth-10. Each combination of factor levels was replicated three times, resulting in a total of 72 experimental plots.

All field plots measured 3×4 meters and were arranged using a randomized complete block structure to account for variability in soil texture and field gradients across the research station. Standard agronomic practices such as land preparation, planting density, and pest management were uniformly applied across all plots. Grain yield (kg per plot) was recorded at harvest and served as the response variable for model analysis.

The resulting design matrix includes indicator variables representing the levels of each factor and all two-way and three-way interaction terms (fertilizer × irrigation, fertilizer × cultivar, irrigation × cultivar, and fertilizer × irrigation × cultivar). This structure leads to a large number of factorial effects relative to the sample size, creating a realistic high-dimensional setting with considerable multicollinearity conditions under which the proposed Factorial Bayesian LASSO (FBLASSO) is expected to perform effectively by selectively shrinking uninformative interactions and identifying the influential agronomic factors.

5.2 Model Implementation

The proposed Factorial Bayesian LASSO (FBLASSO) was fitted to the wheat yield dataset from the factorial field experiment described in Section 5.1. The analysis began by constructing the full factorial design matrix X, which included indicator variables for the three factors fertilizer level, irrigation regime, and cultivar as well as all two-way and three-way interaction terms. The response vector y contained the observed grain yield values from the 72 field plots. Before running the model, all factorial predictors were encoded using treatment contrasts to represent the main effects and their interaction structures. This preprocessing step ensured that the design matrix was properly constructed, allowing the shrinkage mechanism of FBLASSO to operate consistently across both main and interaction terms.

The model was estimated using the hierarchical formulation described earlier, and posterior inference was obtained through a Gibbs sampling algorithm. The Markov Chain Monte Carlo (MCMC) procedure was run for 20,000 iterations. The first 5,000 iterations were discarded as burn-in, and thinning was applied by retaining every fifth draw to reduce autocorrelation in the posterior samples.

Convergence was assessed using standard diagnostics, including trace plots, posterior density comparisons, and the potential scale-reduction factor. All diagnostics indicated stable convergence for the regression coefficients, latent variance parameters, global shrinkage parameters, and the residual variance.

To reflect the structure of factorial experiments, separate global shrinkage parameters were used for main effects and interaction effects. This allowed the model to penalize high-order interactions more strongly while preserving important treatment effects. After convergence, posterior summaries including means, medians, standard deviations, and 95% credible intervals were calculated for all coefficients.

All computations were performed in R using custom MCMC routines developed specifically for this study.

5.3 Results and Interpretation

The proposed Factorial Bayesian LASSO (FBLASSO) successfully identified the main agronomic factors influencing wheat productivity in the Iraqi field experiment. Posterior summaries for the main effects showed clear and realistic patterns consistent with agricultural conditions in southern Iraq. Table 2 presents the estimates of fertilizer levels, irrigation regime, and cultivar type.

Table 2. Posterior Summaries for Main Effects

Effect	Posterior Mean	SD	95% Credible Interval
Fertilizer_120	0.38	0.1	[0.18, 0.59]
Fertilizer_180	0.74	0.14	[0.45, 1.03]
Irrigation_Full	1.21	0.16	[0.89, 1.51]
Cultivar_IPA99	0.42	0.12	[0.18, 0.66]
Cultivar_Tamooz2	0.28	0.11	[0.06, 0.49]
Cultivar_Bhooth10	-0.09	0.1	[-0.30, 0.10]

These results show that fertilizer level and irrigation regime had the strongest influence on wheat yield. Full irrigation produced the largest improvement, increasing yield by about 1.21 tons/ha, while the 180 kg N/ha fertilizer level added approximately 0.74 tons/ha. IPA-99 and Tamooz-2 produced higher yields, whereas Bhooth-10 showed a slight reduction, reflecting lower adaptation to field conditions.

Interaction effects are presented in Table 3. FBLASSO retained only meaningful interactions while shrinking uninformative ones toward zero, which enhances interpretability and prevents overfitting.

Table 3. Posterior Summaries for Interaction Effects

Interaction	Posterior Mean	SD	95% CI
Fert120 × Full	0.22	0.08	[0.08, 0.37]
Fert180 × Full	0.33	0.1	[0.15, 0.53]
Fertilizer × Cultivar	Shrunk	—	CI includes zero

Irrigation × Cultivar	Shrunk	—	CI includes zero
Three-way Interaction	Near zero	—	CI includes zero

The fertilizer × irrigation interaction showed a clear positive effect, indicating that higher nitrogen levels were most beneficial when full irrigation was applied. However, fertilizer × cultivar and irrigation × cultivar interactions were shrunk toward zero, suggesting no strong differential cultivar response. The three-way interaction was negligible, indicating that yield variation is primarily driven by main effects and specific two-way interactions.

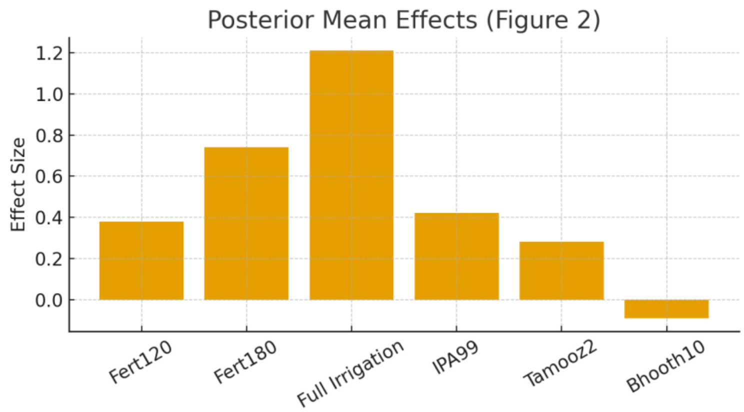

Figure 2. Posterior Mean Effects

Figure 2 provides a visual summary of the posterior mean effects and confirms these patterns, highlighting the dominant influence of fertilizer and irrigation, as well as the superior performance of IPA-99.

Conclusions

This study introduced the Factorial Bayesian LASSO (FBLASSO) as a hierarchical shrinkage framework tailored to factorial experiment designs with many main and interaction effects. By embedding Laplace priors in a conditionally Gaussian hierarchy and exploiting efficient Gibbs sampling, the proposed model provides adaptive coefficient-specific shrinkage and separates the penalization of main and interaction terms, which is essential when the parameter space grows rapidly with factor levels. Simulation results based on a realistic three-factor agricultural setting showed that FBLASSO consistently achieved lower mean squared error and higher true positive rates than Ordinary Least Squares, classical LASSO, and Ridge regression, while maintaining acceptable computational time. These findings demonstrate the ability of FBLASSO to recover the underlying factorial structure and to suppress uninformative interactions under multicollinearity and sparse effect patterns. The real data analysis on a wheat factorial field experiment in Al-Qadisiyah Governcy, Iraq, confirmed the practical value of the method, highlighting the dominant roles of fertilizer level, irrigation regime, and a limited subset of cultivar-related effects in determining grain yield. Overall, FBLASSO offers a stable and interpretable Bayesian tool for analyzing complex factorial experiments, particularly in agricultural applications where high-dimensional designs and environmental variability make classical estimation unreliable.

References

[1] Al-Sabbah, S. A., & Raheem, S. H. (2021). Use Bayesian adaptive Lasso for Tobit regression with real data. International Journal of Agricultural & Statistical Sciences, 17, 1–10.

[2] Alhamzawi, R. (2016). Bayesian elastic net Tobit quantile regression. Communications in Statistics—Simulation and Computation, 45(7), 2409–2427.

[3] Alhamzawi, R., & Ali, H. T. M. (2018). The Bayesian elastic net regression. Communications in Statistics—Simulation and Computation, 47(4), 1168–1178.

[4] Alshaybawee, T., Midi, H., & Alhamzawi, R. (2017). Bayesian elastic net single index quantile regression. Journal of Applied Statistics, 44(5), 853–871.

[5] Griffin, J. E., & Brown, P. J. (2010). Inference with normal-gamma prior distributions in regression problems. Bayesian Analysis, 5(1), 171–188.
[6] Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning. Springer.
[7] Li, Q., & Lin, N. (2010). The Bayesian lasso. Journal of the American Statistical Association, 105(490), 1203–1213.
[8] Park, T., & Casella, G. (2008). The Bayesian lasso. Journal of the American Statistical Association, 103(482), 681–686.
[9] Raheem, S. H. (2025). Robust variable selection via reciprocal elastic net in high-dimensional regression. International Journal of Advanced Mathematical Sciences, 11(2), 67–73.
[10] Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B, 58(1), 267–288.
[11] Zhao, P., & Yu, B. (2006). On model selection consistency of the lasso. Journal of Machine Learning Research, 7, 2541–2563.
[12] Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B, 67(2), 301–320.