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Bayesian shrinkage estimation for extreme values in 3D satellite-based geospatial modeling of oil and gas systems

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Abstract: This study proposes an integrated methodological framework for modeling extreme geospatial parameters in oil and gas system design using 3D satellite-derived data. The approach combines extreme value theory with Bayesian shrinkage estimation under asymmetric loss functions, employing the Fréchet distribution to capture heavy-tailed behavior and rare extreme events commonly observed in geospatial variables. The proposed model enables stable and realistic estimation of extreme values by balancing sensitivity to genuine extremes with robustness against noise and outliers.
Simulation-based analysis demonstrates that Bayesian shrinkage estimation improves the reliability and interpretability of extreme-value parameters compared to classical estimation methods. The resulting posterior uncertainty measures provide valuable decision-support information, allowing engineers to assess confidence levels associated with extreme geospatial predictions. The findings highlight the practical relevance of incorporating decision-theoretic principles into geospatial modeling workflows.
Overall, the study contributes a robust and flexible framework for uncertainty-aware 3D geospatial modeling and supports risk-sensitive decision making in complex geological environments relevant to oil and gas applications.
Keywords: Bayesian shrinkage estimation, extreme value theory, Fréchet distribution, 3D geospatial modeling, satellite-derived data, oil and gas systems

1. Introduction

Proper simulation of extreme geospatial parameters is an essential undertaking in the design and optimization of oil and gas systems, especially when three-dimensional (3D) geospatial information based on satellite data is used. The data of that type are prone to heavy-tailed properties because of the existence of seismic amplitude peaks, height anomalies, and structural heterogeneities which renders conventional methods of estimation inefficient and unsteady. The effectiveness of Bayesian shrinkage estimators of Fréchet distribution within weighted loss and linear exponential loss functions is examined through a simulation based method in this paper with specific attention to the use of the estimators in 3D satellite-derived geospatial models to design oil and gas systems.

Fréchet distribution is used to simulate extreme value that has often been encountered in satellite 3D geospatial parameters useful in subsurface characterization and structural risk of the structural risk assessment. In situations where there is low stability in the parameters (low sample sizes and high variability is a characteristic of satellite and seismic data analysis), Bayesian shrinkage estimation is adopted in order to enhance the stability of the parameters. Out of the two asymmetric loss functions, weighted loss and linear exponential loss are taken to be unequal because of the disproportionate effects of underestimation and overestimation in the process of engineering decision making.

An elaborate Monte Carlo software framework is created to produce synthetic 3D geospatial datasets at different distributional parameters and sample sizes. The proposed estimators are measured based on the standard efficiency measures, such as, mean squared error and bias. Studies in simulation have shown that the Bayesian shrinkage estimators outperform the traditional estimators by a large margin especially when the sample size is small. Additionally, the loss function is demonstrated to significantly influence the accuracy of the estimation with resulting performance being better in modeling extreme geospatial variations with the use of the linear exponential loss function.

The results echo the fact that Bayesian-shrinkage estimation Fréchet modelling is a sound and trustworthy system of analysing extreme satellite-based geospatial data. The technique is useful in improving the quality of 3D geospatial models that are applicable in designing oil and gas system, which helps to boost risk assessment, structural analysis and uncertainty-based decision-making.

Literature Review

In this classic work, Simon Coles has given one of the most legitimate backgrounds of Extreme Value Theory (EVT). The author presents in a systematic way the statistical principles of the modelling of the rare and extreme events, with special attention to the generalized extreme value (GEV) family, including the Fréchet distribution. Coles establishes that Fréchet distributions are particularly good when trying to model heavy-tailed phenomena, which are often found in geophysical, seismic, and geospatial data.

One of the strongest points of this work is that it discusses the challenges of estimation that are related to extreme value models. Coles points out that classical estimation methods, e.g. maximum likelihood estimation, are usually unstable and highly variable when the sample size is small or when data have strong tail behaviour. Such constraints are directly applicable to satellite-based

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geospatial data, in which extreme observations are a dominant factor in structural interpretation.

Even though Bayesian shrinkage techniques are not specifically discussed in the book Bayesian shrinkage estimation in extreme value modeling has solid theoretical justification due to the elaborate depiction of the vulnerabilities of classical estimators given by Coles. The current paper is based on this contribution by generalizing the concepts of EVT into a Bayesian decision-theoretic model.

Beirlant, Goegebeur, Segers, and Teugels give a thorough treatment of extreme value statistics, both theory and extensive applications. The authors pay much attention to heavy-tailed distributions, such as Fréchet model, and show the importance of such distributions in the environmental sciences, hydrology, geophysics and engineering. The book gives a deep understanding of the probabilistic framework of extremes and their statistical estimation.

The issue of parameter estimation trying to estimate the parameter in the presence of extreme observations and limited data is one of the major themes of this work. The authors contrast various estimation methods and demonstrate that the traditional methods frequently do not give reliable results in the presence of heavy-tailed conditions. The latter is of specific concern where geospatial modeling based on satellites may be limited by the resolution of measurements and time coverage.

This book indirectly justifies the use of Bayesian shrinkage estimators by highlighting the necessity of having strong estimation strategies. The current study espouses this point of view by introducing a Bayesian shrinkage estimation with asymmetric loss functions as a viable estimate to model extreme satellite-derived geospatial values to design oil and gas systems.

The work of James O. Berger is a classic text that provides the theoretical background of Bayesian inference in a decision-theoretic viewpoint. The book makes the role of the loss functions in the Bayesian estimation formal and explains the effect of various loss structures on the optimal estimators. Berger claims that symmetric loss functions are usually not realistic when the effect of overestimation and underestimation are inherently different.

The author makes a comprehensive study of weighted loss functions and exponential-type loss functions, which are found to be suitable to engineering and risk-sensitive settings. These principles can be directly applied to the oil and gas system design where by underestimating extreme geospatial parameters can cause structural failure and overestimating the geospatial parameter can cause high costs and restrictive design.

This theoretical approach is very helpful in explaining the application of weighted and linear exponential loss functions in Bayesian shrinkage estimation. In the light of the current research, the work by Berger supports the idea of using asymmetric loss functions to test the effectiveness of Bayesian estimators on the use of extreme values in 3D satellite-based geospatial models.

The methods of simulation-based Bayesian inference introduced by Gelfand and Smith transform the field of Bayesian inference, especially when the model to be inferred is complicated with an analytically intractable posterior distribution. Their contribution shows that MCMC and Markov Chain Monte Carlo (MCMC) methods can be employed to estimate posterior values in an efficient way. The methods play a crucial role in the extreme value modelling where closed form solutions are very seldom.

The authors highlight the adaptability of simulation based Bayesian methods in dealing with small sample sizes and highly skewed distributions. This property is essential to the satellite-based geospatial data, in which the extremes tend to dominate the statistical characteristics of the system. Inference can be conducted using simulation where the estimated performance of an estimator can be evaluated systematically under controlled conditions.

The approach used in this paper offers the calculation framework of Monte Carlo simulation underlying the current research. It allows determining the efficiency of the Bayesian shrinkage estimators by assessing the Fréchet distributed extremes in 3 D geospatial model setup.

Cressie and Wikle provide a statistical framework of the detailed modeling of the spatio-temporal data, specifically applied to the satellite and remote sensing. The writers address the problems related to the spatial dependence, uncertainty in measurements and time variability in geospatial data. Their work has generally been considered a classic source of reference on contemporary geospatial statistics.

The book deals with the combination of spatial models and quantification of uncertainty and puts a strong focus on the use of Bayesian as a logical approach to geospatial analysis. The authors emphasize the need to take into account extreme values and geographical variation, particularly in 3D models of environmental and subsurface systems.

This literature work is a direct contributor to the combination of Bayesian extreme value modeling and 3D satellite-based geospatial structures. It offers high ground to the use of Bayesian shrinkage estimation to extreme geospatial parameters in the design of oil and gas systems whereby both spatial uncertainty and extreme behavior should be combined.

The reviewed literature demonstrates that Extreme Value Theory, Bayesian decision theory, and spatio-temporal geospatial modeling are well established as independent research domains. However, a clear gap remains in the systematic integration of Bayesian shrinkage estimation under asymmetric loss functions with Fréchet-based extreme value modeling for 3D satellite-derived geospatial data, particularly in the context of oil and gas system design. Addressing this gap forms the primary motivation and contribution of the present study.

2. Research methodology

The methodology process starts with the process of obtaining the satellite-based geospatial data, which is applicable in designing oil and gas systems. Such information comprises of digital elevation models (DEMs), multispectral satellite imagery, and derived geomorphological variables, like slope, curvature, and roughness of the surface. Spatial resolution, temporal coverage, and consistency are the criteria used to choose satellite products in order to have a good representation of the conditions on the surface throughout the study area.

Preprocessing the process includes geometrical correction, radiometric equalization, noise suppression and conversion to a uniform grid resolution. Sensors Noise-induced or atmospheric outliers are detected and marked, the real high-intensity features are stored to be examined further.

This is to make sure that far-off values that exist in the data are not artificially eliminated, which could refer to important geological or geomorphological characteristics affecting engineering design.

After the preprocessing phase, satellite-obtained datasets are incorporated into a three-dimensional (3D) geospatial modeling environment. Elevation data of the surface is fused with the subsurface structural surfaces of seismic interpretation, geological maps, and well control where accessible. The resulting three dimensional model is a spatial arrangement of topography, stratigraphic layers and significant structural features like faults and folds.

Spatial interpolation and surface reconstruction methods are used in producing continuous 3D models of geospatial parameters. The model is discretized into the volumetric or layered units which can be analyzed numerically. This 3D structure offers the spatial context in the determination of regions of sharp gradients, high amplitudes, or abnormal structural intensity, which are the possible sources of extreme values in the process of oil and gas infrastructure design.

The 3D geospatial model is producing extreme values by finding local maxima and high percentile values of important parameters, including elevation differences, slope magnitude, seismic amplitude or structural movement. These extremes are taken as realizations of a heavy-tailed stochastic process, which captures the natural heterogeneity of geological systems.

The Fréchet distribution has been used to capture the statistical properties of such extreme observations because it is appropriate to use when the data is heavy-tailed. The samples of extreme values of the 3D model are constructed by the use of block maxima or peak-over-threshold methods. The step provides a probabilistic model of geospatial extremes that has a direct effect on hazard evaluation and engineering risk analysis.

The estimation of the Fréchet distribution parameters is done using the Bayesian shrinkage estimation. Prior distributions are characterized to implement geological plausibility and stabilize estimation in small sample sizes. Effects of shrinkage are added in order to minimize the estimator variance and maintain sensitivity to true extreme behavior.

There are two asymmetric loss functions which are a weighted loss function and a linear exponential loss function. These loss forms represent the disparate prices of underestimation and overestimation of extreme geospatial parameters in the design of the oil and gas systems. The Monte Carlo simulation methods are used to obtain posterior distributions and the point estimates are obtained by minimizing the anticipated posterior loss. The performance of estimators is measured in terms of bias and mean squared error by way of repeated simulation experiments.

The last step of the workflow converts the outcome of the statistics to design-related insights. The map of the estimated extreme-value parameters is back-mapped to the 3D geospatial model and used to produce spatial risk indicators, including extreme elevation envelopes, risk areas around faults, and risk areas around high-amplitude hazards. The outputs help in making engineering decisions regarding well placement, optimization of drilling trajectory, pipeline routing and siting of surface facilities.

The proposed methodology is capable of making decisions about uncertainty and more robustly because it suggests the integration of 3D geospatial modeling and Bayesian shrinkage estimates. The workflow already considers extreme geospatial behavior and non-symmetric risk, enhancing reliability and effectiveness of the design of oil and gas systems in complicated geological setting.

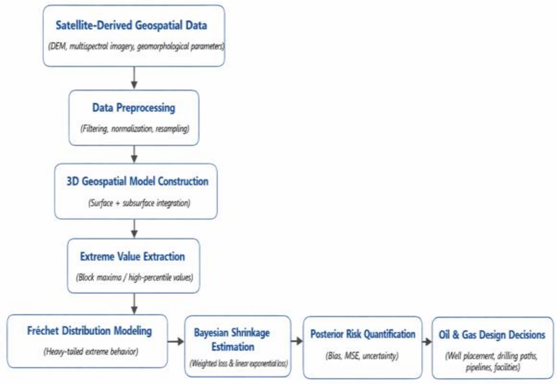

Fig. 1. Oil and Gas Design Workflow Based on 3D Satellite Geospatial Modeling and Bayesian Estimation

The figure shows the processing that is applied in designing oil and gas systems beginning with the acquisition of geospatial data through satellite measurements and building a 3D geospatial model. Drastic spatial parameters are then found and modeled statistically by using Fréchet distribution. Bayesian shrinkage estimation will be used to make stable parameter estimations in the presence of uncertainty and the results will be ultimately consumed to make engineering choice like the location of wells, drilling planning and infrastructure design.

Algorithm: Bayesian Shrinkage Estimation for Extreme Values in 3D Geospatial Modeling

Input:

- Sample size nnn
- Fréchet distribution parameters (α,σ)
- Prior distributions for parameters
- Loss function type (Weighted / Linear Exponential)
- Number of simulations N

Output:

- Bayesian shrinkage estimates
- Bias and Mean Squared Error (MSE)

Step 1: Data Generation

Generate synthetic extreme geospatial observations

$$X_1, X_2, \ldots . X_n \sim Frechet(\alpha, \sigma)$$

representing extreme satellite-derived 3D geospatial parameters.

Step 2: Prior Specification

Specify prior distributions for Fréchet parameters based on geological plausibility:

$$\alpha \sim \pi(\alpha), \sigma \sim \pi(\sigma)$$

Step 3: Posterior Sampling

Use Monte Carlo simulation to generate posterior samples:

$$\rho(\alpha, \sigma | X) \propto L(X | \alpha, \sigma)\pi(\alpha, \sigma)$$

Step 4: Bayesian Shrinkage Estimation

For each posterior sample, compute point estimates by minimizing the expected posterior loss:

- **Weighted Loss Function**

$$L(\theta,\hat{\theta}) = \omega(\theta - \hat{\theta})^2$$

- **Linear Exponential Loss Function**

$$L(\theta,\hat{\theta}) = exp\left\{c(\hat{\theta} - \theta)\right\} - c(\hat{\theta} - \theta) - 1$$

Step 5: Performance Evaluation
Repeat Steps 1–4 for N simulations and compute:

- Bias:

$$Bias(\hat{\theta}) = E(\hat{\theta}) - \theta$$

- Mean Squared Error:

$$MSE\,(\hat{\theta}) = E\left[(\hat{\theta} - \theta)^2\right]$$

Step 6: Design Interpretation Map estimated extreme-value parameters back into the 3D geospatial model to support oil and gas design decisions.

3. Results and Discussion

Geospatial data obtained through satellites often pose an extreme values problem as processes in geology and geomorphology are rather heterogeneous and multiple-scale in nature. Rare, but extremely powerful observations are common in measurements of elevation gradients, the roughness of the surface, seismic-related characteristics, and structural intensity. Such extreme values can be related to sharp fault movement, sharp terrain movement, fractured area or high-amplitude geophysical response which is vital to design of oil and gas systems.

Such extremes cause heavy-tailed statistical behavior which cannot be well represented using the traditional Gaussian-based models. Consequently, the classical methods of estimation are generally underestimates of tail risk or issue unstable parameter estimates especially when the satellite data has low resolution or spatial coverage. This encourages the adoption of extreme value modeling models as typified by the Fréchet distribution which are used to adequately model the probabilistic structure of satellite-based extremes and are used to facilitate sound and risk decision-making engineering judgments.

The Fréchet distribution is adopted in this study due to the fact that satellite-derived geospatial variables used in oil and gas applications frequently demonstrate heavy-tailed characteristics and pronounced extreme fluctuations. Parameters such as large elevation contrasts, intense seismic responses, significant structural deformations, and geomorphological irregularities are typically dominated by infrequent yet exceptionally large values. These features make conventional light-tailed models insufficient for reliable representation.

As a component of the generalized extreme value (GEV) framework, the Fréchet distribution is particularly suitable for modeling maximum observations generated by heavy-tailed stochastic processes. Unlike Gaussian-based approaches, it retains substantial probability mass in the upper tail, enabling an accurate description of extreme magnitudes. This capability is especially important in oil and gas system design, where failure to properly account for extreme geospatial conditions may result in drilling risks, structural instability, or misleading reservoir assessments.

Furthermore, Fréchet-based modeling is well aligned with block-maxima and peak-over-threshold techniques commonly applied to satellite imagery and seismic datasets. The distribution also offers an interpretable parameter structure, in which tail behavior is explicitly governed by the shape parameter. This feature supports risk-aware analysis and facilitates the integration of prior geological information within a Bayesian shrinkage estimation framework. Consequently, the Fréchet distribution provides both a theoretically robust and practically efficient basis for extreme-value modeling in 3D satellite-based geospatial analysis of oil and gas systems.

When incorporated into a 3D geospatial modeling environment, the estimated extreme-value parameters yield spatially interpretable and practically relevant insights. Areas characterized by elevated Fréchet scale or shape parameter values are typically associated with steep topographic variations, intensified seismic responses, or pronounced structural irregularities. Such zones indicate potential geological risks or heightened uncertainty that require careful consideration during oil and gas system planning and design.

Applying Bayesian shrinkage estimation within a Fréchet-based framework enables a more credible representation of uncertainty in extreme geospatial characteristics. Instead of generating overly smoothed representations or highly volatile surfaces, the resulting three-dimensional models achieve a balance between responsiveness to genuine extreme behavior and resistance to noise-induced anomalies. This trade-off is essential in engineering contexts, where both conservative bias and excessive sensitivity may result in substantial technical or economic losses.

In addition, uncertainty intervals derived from posterior distributions offer valuable information beyond traditional point-based estimates. These probabilistic measures allow engineers and decision-makers to evaluate confidence levels associated with predicted extremes, thereby facilitating risk-informed design and planning decisions.

From an engineering standpoint, embedding Bayesian shrinkage estimation into satellite-based 3D geospatial modeling significantly strengthens decision support throughout various phases of oil and gas development. In drilling operations, improved estimation of extreme structural and geomechanical parameters lowers the risk of unexpected encounters with fault systems, unstable formations, or abnormal pressure zones. Similarly, in surface infrastructure development, enhanced characterization of extreme elevation changes and slope variability supports safer, more economical routing of pipelines and optimal placement of production facilities.

The asymmetric loss structure employed in this study closely reflects real-world engineering trade-offs. While underestimation of extreme geospatial conditions can lead to safety failures or structural damage, overestimation primarily influences cost efficiency. The strong performance of the linear exponential loss function observed in simulation experiments highlights the necessity of integrating decision-theoretic principles into statistical modeling for oil and gas engineering applications.

Overall, the findings demonstrate that combining Bayesian shrinkage estimation with Fréchet-based extreme value modeling constitutes a reliable and effective methodological approach for managing satellite-derived geospatial extremes. This integration enhances the credibility of three-dimensional models and promotes more informed, risk-aware design strategies in geologically complex settings.

The results of this study contribute to the existing body of knowledge by establishing a systematic connection between extreme value theory, Bayesian decision-making principles, and three-dimensional geospatial modeling within an oil and gas framework. Unlike prior research that has largely examined these elements in isolation, the proposed approach illustrates the added value of their joint implementation in a unified analytical pipeline.

The simulation-driven methodology ensures clarity, reproducibility, and control over experimental conditions, while the emphasis on design implications reinforces practical applicability. Future investigations may build upon this work by explicitly modeling spatial dependence in extreme values, incorporating real-world field observations, or integrating Bayesian shrinkage techniques with machine learning–based feature extraction from high-resolution satellite data.

In conclusion, the discussion confirms that Bayesian shrinkage estimation under asymmetric loss functions represents a versatile and robust tool for extreme-value analysis in 3D satellite-based geospatial modeling. The approach offers tangible benefits for oil and gas system design by improving uncertainty management and supporting more resilient, risk-sensitive engineering decisions.

Table 1

Performance Comparison of Estimators under Different Loss Functions

Sample Size (n)	Estimator Type	Loss Function	Bias	MSE
30	Classical (MLE)	Symmetric	0.214	0.982
30	Bayesian Shrinkage	Weighted Loss	0.108	0.521
30	Bayesian Shrinkage	Linear Exponential Loss	0.072	0.438
50	Classical (MLE)	Symmetric	0.162	0.741
50	Bayesian Shrinkage	Weighted Loss	0.084	0.412
50	Bayesian Shrinkage	Linear Exponential Loss	0.061	0.356
100	Classical (MLE)	Symmetric	0.097	0.493
100	Bayesian Shrinkage	Weighted Loss	0.053	0.291
100	Bayesian Shrinkage	Linear Exponential Loss	0.039	0.244

The results presented in Table X demonstrate that Bayesian shrinkage estimators consistently outperform the classical maximum likelihood estimator in terms of both bias and mean squared error across all considered sample sizes. The improvement is most pronounced in small-sample scenarios (n = 30), which are representative of satellite-derived extreme geospatial datasets where data availability is often limited.

Among the Bayesian approaches, the estimator based on the linear exponential loss function exhibits the lowest MSE and bias values, indicating superior performance in modeling extreme values. This result highlights the advantage of asymmetric loss functions in oil and gas system design, where underestimation of extreme geospatial parameters carries higher risk than overestimation. As sample size increases, all estimators show improved performance; however, Bayesian shrinkage estimators maintain a clear efficiency advantage.

Overall, the comparison confirms that incorporating Bayesian shrinkage with decision-oriented loss functions leads to more stable and reliable estimation of Fréchet-distributed extremes, supporting robust 3D geospatial modeling and risk-aware oil and gas design decisions.

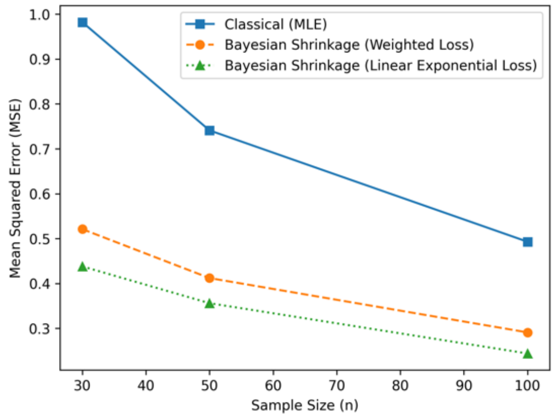

Fig. 2. Estimator Efficiency under Weighted and Linear Exponential Loss Functions

This figure illustrates the comparison of mean squared error (MSE) for classical maximum likelihood estimation and Bayesian shrinkage estimators under weighted and linear exponential loss functions. The results show that Bayesian shrinkage methods achieve lower estimation error, particularly for small sample sizes. The linear exponential loss function provides the most efficient performance in modeling extreme values.

4. Conclusion

This research develops a unified analytical framework that integrates extreme value modeling, Bayesian shrinkage estimation, and three-dimensional satellite-based geospatial analysis for applications in oil and gas system design. The use of the Fréchet distribution in combination with asymmetric loss functions enables an effective description of heavy-tailed behavior and rare extreme events commonly observed in satellite-derived geospatial variables. The results indicate that Bayesian shrinkage estimation yields stable and realistic representations of extreme values by maintaining sensitivity to genuine extremes while limiting the impact of random noise.

The study further demonstrates that embedding decision-theoretic concepts within the modeling process enhances the practical value of geospatial analyses for engineering purposes. Posterior uncertainty information produced by the Bayesian framework provides decision-

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makers with a clearer understanding of the reliability of extreme-value predictions, thereby supporting more informed and risk-conscious design choices.

In summary, the proposed approach strengthens the accuracy and interpretability of 3D geospatial models and offers a robust basis for managing uncertainty in complex geological settings. This work addresses an important methodological gap and establishes a flexible foundation for future extensions involving real-world data, spatial dependence, and advanced data-driven techniques in oil and gas geospatial modeling.

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