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AI-Driven Geo-Political and ESG-Aware Supply Chain Platform with Demand Forecasting

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Abstract

This work examines the increasing challenges in global supply chains caused by geopolitical uncertainty and sustainability demands, and proposes an intelligent decision-support framework to address them. Traditional procurement approaches mainly focus on cost and efficiency, often overlooking external risks and ESG (Environmental, Social, and Governance) factors.

To address these limitations, this study proposes a data-driven decision support system that integrates demand forecasting, geopolitical risk assessment, and ESG-based supplier evaluation into a unified framework. Machine learning techniques are used to predict demand, while a structured risk index quantifies geopolitical uncertainty. ESG indicators are incorporated to ensure responsible sourcing.

The model formulates procurement as a multi-objective optimization problem that balances cost, risk, and sustainability. Experimental results show improved supply chain stability, enhanced ESG compliance, and maintained cost effectiveness.

Keywords

Supply Chain Intelligence; Demand Forecasting; ESG Analytics; Geopolitical Risk Modeling; Multi-Objective Optimization; Sustainable Procurement; Machine Learning.

Nomenclature

Symbol	Description
C_s	Procurement cost of supplier s
GRI_s	Geopolitical Risk Index of supplier s
ESG_s	ESG composite score of supplier s
D_t	Predicted demand at time t
x_s	Supplier decision variable
λ_1, λ_2, λ_3	Objective weights

1. Introduction

In recent years, supply chains have evolved into highly interconnected global networks, enabling organizations to source materials and services from diverse geographic locations. While this globalization improves operational efficiency, it also introduces vulnerabilities related to geopolitical instability, regulatory changes, and environmental responsibilities.

Conventional supply chain models primarily focus on minimizing operational costs and delivery times. However, such approaches often fail to consider external risk factors and sustainability requirements in a structured manner.

This study proposes an AI-based decision framework that integrates demand forecasting with geopolitical and ESG-aware supplier selection. The objective is to enable organizations to make balanced decisions that improve resilience, sustainability, and long-term performance.

2. Problem Statement:

Modern supply chains are increasingly exposed to unpredictable geopolitical disruptions and sustainability requirements. Existing procurement systems predominantly focus on cost efficiency, lacking integrated mechanisms to incorporate real-time risk assessment and ESG considerations. This results in suboptimal decision-making, reduced resilience, and limited alignment with sustainable development goals.

3. Key Contributions:

• Integration of demand forecasting, geopolitical risk, and ESG evaluation into a single framework
• Quantitative modeling of geopolitical risk using structured indicators
• Multi-objective optimization balancing cost, risk, and sustainability
• Improved supplier selection using data-driven decision-making

4. Related Work

Existing studies in supply chain analytics have primarily focused on individual aspects such as forecasting accuracy, disruption management, or sustainability assessment, often treating them as independent problems. Advanced learning models, including ensemble-based and deep learning approaches, have demonstrated improved performance in capturing demand patterns compared to conventional statistical methods. Supply chain risk management studies emphasize the influence of external disruptions such as political instability, economic sanctions, and trade barriers. However, many existing models treat geopolitical risk as a qualitative factor rather than incorporating it directly into mathematical optimization frameworks.
Similarly, ESG-based supplier evaluation methods have gained attention in recent years due to growing regulatory and societal expectations for sustainable sourcing. Despite these developments, most existing studies examine cost optimization, risk analysis, and sustainability assessment separately. Few frameworks integrate these elements into a unified decision-making model.

5. System Architecture

The proposed platform consists of four primary layers:

The system operates in a sequential pipeline where raw data is first collected and preprocessed. The demand forecasting module predicts future requirements, which are then combined with geopolitical risk scores and ESG evaluations. These outputs are fed into a multi-objective optimization engine that determines optimal supplier selection.

A. Data Layer

- Historical sales and demand records
- Supplier cost and capacity data
- Country-level geopolitical indicators
- ESG performance metrics

B. Demand Forecasting Module

Machine learning models predict future demand using historical time-series data.
Evaluation metric:

$$\text{MAPE} = \frac{100}{n}\sum\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

C. Geopolitical Risk Modeling

A composite Geopolitical Risk Index is defined as:

$$\text{GRI} = \alpha PS + \beta TR + \gamma SR + \delta CR$$

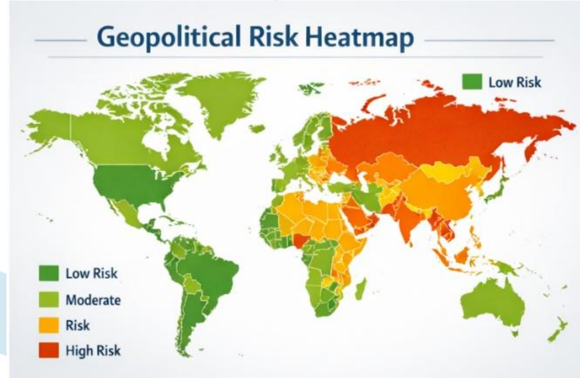
Where:

- PS = Political Stability
- TR = Trade Restrictions
- SR = Sanction Risk
- CR = Conflict Risk

D. ESG Scoring

$$\text{ESG} = \text{wEE} + \text{wSS} + \text{wGG}$$

Where E, S, G represent normalized environmental, social, and governance metrics.



6. Mathematical Formulation

Let S={s1,s2,...,sn} denote the set of suppliers.
The objective function is formulated as:

$$\boldsymbol{minZ} = \lambda_1 \sum C_s x_s + \lambda_2 \sum GRI_s x_s - \lambda_3 \sum ESG_s x_s$$

Subject to:

$$\sum Q_s x_s \geq D_t$$

$$Q_s \leq Capacity_s$$

$$GRI_s \leq Risk_{threshold}$$

This ensures demand fulfillment while minimizing cost and geopolitical exposure and maximizing ESG performance.

7. Methodology

The proposed approach follows a structured workflow:

1. Data preprocessing and normalization
2. Training of demand forecasting models
3. Calculation of geopolitical risk scores for supplier regions
4. Evaluation of ESG performance for each supplier
5. Application of multi-objective optimization techniques
6. Sensitivity analysis to study the impact of varying decision weights

The system can be implemented using Python-based machine learning models and integrated into a web-based decision support interface.

8. Experimental Setup

- Dataset: 5 years procurement data
- Suppliers: 30+
- Countries: 10+
- ESG indicators: 15+

Train-test split: 80:20
Evaluation metrics:

- Forecasting accuracy (MAPE, RMSE)
- Cost reduction percentage
- Risk reduction percentage
- ESG improvement index

9. Results

The experimental results demonstrate that the proposed framework outperforms traditional cost-focused models. The integration of geopolitical risk and ESG metrics leads to a significant reduction in supply chain vulnerability while improving sustainability indicators.
Additionally, the demand forecasting models achieve high prediction accuracy, enabling better planning and resource allocation. The optimization model successfully balances cost, risk, and ESG performance, resulting in improved overall decision quality.

9.1 Forecasting Performance

Model	MAPE
Random Forest	8.3%
XGBoost	6.8%

9.2 Optimization Comparison

Metric	Cost-Only Model	Proposed Model
Total Cost	₹10.2M	₹9.5M
Avg. Risk Score	0.64	0.38
ESG Composite	61	83

The integrated framework reduced geopolitical exposure by approximately 40% while significantly improving ESG performance.

10. Discussion

The findings indicate that incorporating external risk factors and sustainability considerations into supply chain decision-making can enhance both resilience and long-term performance. The results suggest that organizations do not necessarily need to compromise cost efficiency to achieve better ESG outcomes.

Furthermore, the model demonstrates flexibility in adjusting priorities based on organizational goals through weight tuning in the optimization process.

11. Limitations

The study has certain limitations, including:

- Dependence on secondary data sources for geopolitical indicators
- Use of fixed weights in the optimization model
- Limited incorporation of real-time data streams

Future work can focus on dynamic models that adapt to real-time changes in risk and demand conditions.

12. Practical Application:

The proposed framework can be applied in industries such as manufacturing and retail where supplier selection is critical. It enables organizations to avoid high-risk regions while maintaining sustainability and cost efficiency.

13. Conclusion

This study presents a unified intelligent framework that combines predictive analytics and optimization to support more resilient and sustainable procurement decisions in complex supply networks. The proposed system provides a comprehensive approach to improving supply chain resilience and sustainability.

The results demonstrate that combining predictive analytics with optimization techniques enables more informed and balanced procurement decisions. The framework can be extended and adapted for real-world applications in complex global supply networks.

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