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Geopolitical Risk Prediction and Robust Investment Decision-Making for Transnational Photovoltaic Projects in Africa via Generative AI and Spatiotemporal GNN

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Abstract Geopolitical risks associated with transnational photovoltaic (PV) projects in Africa are dynamic, interconnected, and difficult to assess using conventional investment models. Specifically, existing approaches often struggle to characterize cross-border risk transmission and incorporate evolving geopolitical information into investment decisions. To address these challenges, this study proposes EG-GeoInvest, a framework that integrates generative artificial intelligence (AI) with spatiotemporal graph neural networks for geopolitical risk assessment and risk-aware investment decision-making. First, geopolitical event records, multilingual news, national governance indicators, and PV investment data are combined within an evidence-constrained, multisource heterogeneous information system to support the identification and semantic representation of risk events. Second, a Spatiotemporal Geopolitical Risk Encoding Module (ST-GREM) integrates a temporal convolutional network with relationship-aware graph convolution to represent the evolution of risks and their interdependencies across transnational investment, energy-trade, and financing networks. Third, cross-modal semantic projection and Low-Rank Adaptation (LoRA) enable graph-structured information and generative language models to contribute jointly to forecasts of geopolitical risks, project delays, and economic loss distributions. Finally, the predicted risk distributions inform a Conditional Value-at-Risk (CVaR) and distributionally robust optimization framework for investment allocation under return and tail-risk constraints. A proposed evaluation design encompassing comparative risk prediction, cross-country generalization, and investment scenario analysis provides a basis for assessing predictive performance and potential decision-making value.

Index Terms generative artificial intelligence; geopolitical risks; solar investment in Africa; spatiotemporal graph neural networks; transnational risk transmission; distribution-robust optimization

I. Introduction

Amid the accelerating global energy transition and efforts to achieve carbon neutrality, solar photovoltaic (PV) power has become an important option for expanding electricity access and supporting low-carbon development. In Africa, growing electricity demand, inadequate conventional power infrastructure, and substantial solar resources create opportunities for PV deployment. The International Energy Agency (IEA) reported that Africa possesses approximately 60% of the world's best solar resources but accounted for only about 1% of installed global solar PV capacity at the time of its 2022 assessment [1]. This contrast illustrates the gap between renewable-energy potential and realized deployment. Investment, however, is constrained by scarce capital, relatively high financing costs, and differences in political and regulatory environments. Under the IEA's Sustainable Africa

Scenario, annual energy investment would need to exceed \$200 billion by 2030 to meet the continent's energy access and climate objectives; total energy investment in 2022 was below \$90 billion, of which approximately \$25 billion was directed toward clean energy [2]. These conditions underscore the need for rigorous PV investment appraisal that accounts for geopolitical uncertainty, project exposure, and competition for limited financial resources. Such analysis is relevant to energy security, regional economic development, international climate finance, and the Sustainable Development Goals.

As the division of labor within the global photovoltaic industry chain deepens and the scale of international capital flows expands, African photovoltaic projects are gradually forming a complex network of cooperation involving host-country governments, foreign investors, international financial institutions, equipment suppliers, and cross-border electric-

ity trading entities. Unlike typical domestic energy projects, cross-border PV investments are generally characterized by large capital outlays, long payback periods, high asset specificity, and high exit costs. Their economic feasibility depends not only on solar irradiation resources, installed capacity, power generation efficiency, and construction costs, but is also influenced by a combination of factors such as the host country's political stability, the continuity of energy policies, cross-border trade regimes, foreign exchange market volatility, and international financing conditions. Particularly in regions of Africa where there are significant disparities in political and economic development, localized political conflicts, adjustments to government policies, border controls, or international financial restrictions may affect photovoltaic investment projects in multiple countries through channels such as equipment supply, capital flows, and cross-border energy transactions, transforming risks that were originally confined to a single country into investment uncertainties with transnational implications. Therefore, risk analysis for transnational photovoltaic projects in Africa cannot be limited to a static assessment of political risks in the host country; rather, it must fully account for dynamic shifts in geopolitical events, structural dependencies within transnational economic relationships, and their differentiated impacts on the economic outcomes of the projects.

Existing research has examined the external constraints on renewable energy development in Africa from the perspectives of energy system planning, investment environment assessment, and political risk management. Trotter et al. [3] incorporated political risk factors into a dual-objective optimization model for African power systems. Their findings indicate that cross-border power grids designed solely to minimize system costs may face higher political risks, whereas appropriately increasing the share of local solar power generation can help reduce reliance on large-scale power exports from politically unstable countries. The study further indicates that, under specific 2030 optimization scenarios, a moderate increase in energy system costs can significantly reduce avoidable political risks, providing an important basis for understanding the trade-off between the efficiency of cross-border energy trade and energy security. Baumli and Jamasb [4] employed a multi-criteria decision-making analysis to examine the determinants of private renewable energy investment in Africa, emphasizing the crucial role of regulatory effectiveness, the quality of power purchase agreements, and the policy environment in investor decision-making. Jiang et al. [5] further examined the relationship between political risk in developing countries and foreign renewable energy investment, noting that project vulnerability and the capabilities of multinational enterprises may alter the effects of different types of political risk. Focusing on sub-Saharan Africa, Villar-Roldán et al. [6] used panel data to analyze the relationship between economic, political, and institutional factors and renewable energy development, revealing the importance of factors such as national governance, economic conditions, and energy accessibility. These studies indicate that geopolitical and institutional risks have become

key variables in explaining disparities in renewable energy investment across Africa. However, existing analyses have primarily focused on identifying macro-level influencing factors, conducting static investment evaluations, or examining energy system configurations under specific scenarios. Further research is therefore needed to identify high-frequency risk events, model transnational risk interdependencies, and forecast risks at the individual PV-project level.

An additional challenge is translating political risk into project-level economic losses and investment valuation parameters. Economic evaluations of traditional energy projects typically use methods such as Net Present Value (NPV), Internal Rate of Return (IRR), or risk-adjusted discount rates to assess investment feasibility. However, the political risks faced by cross-border photovoltaic investments are often characterized by uncertainty regarding the timing of their occurrence, varying durations of impact, and heterogeneous levels of project exposure; a single risk premium or fixed discount rate may not fully reflect their actual impact. Shimbar and Ebrahimi [7] studied the valuation of political risks in renewable energy projects in developing countries. They proposed combining risk pricing with an investment decision tree and emphasized the need to reasonably distinguish between cash flow risk and discount rate adjustments to avoid valuation biases caused by traditional risk-adjusted discount rate methods. Calcaterra et al. [8] incorporated country- and technology-specific capital costs into an energy economics model, revealing the significant impact of financing conditions on the deployment of clean energy and the costs of energy transition in developing countries. Dato et al. [9] further examined variations in the weighted average cost of capital (WACC) across the electricity sectors of 48 African countries, demonstrating significant heterogeneity in financing conditions among African nations. These studies provide a theoretical and empirical foundation for quantifying the economic consequences of geopolitical risks. However, existing investment valuation methods typically rely on preset risk parameters or relatively low-frequency macroeconomic variables, making it difficult to fully leverage continuously updated information on geopolitical events to make dynamic probabilistic forecasts of potential construction delays, cost overruns, and cash flow losses that different projects may face in the future.

Geopolitical risk has traditionally been measured using expert assessments, national governance indicators, political risk ratings, and news text analysis to construct risk indices. Caldara and Iacoviello proposed the Geopolitical Risk Index (GPR) based on news texts, incorporating geopolitical threats and actual adverse events into a unified measurement system, and found that higher geopolitical risk is associated with reduced investment and employment. This study provides an important methodological foundation for the long-term measurement of geopolitical risk and the analysis of its economic impacts [10].

However, risk measurement methods based on predefined dictionaries and keyword matching have certain limitations in capturing the semantics of complex events, relation-

ships among transnational actors, and the nuances of policy changes. For example, a single news story may simultaneously involve military threats, international sanctions, disruptions in energy supply, and diplomatic negotiations, yet the nature of the impact and economic consequences of these different events on photovoltaic projects may vary significantly. Simply relying on keyword frequency may not only overlook the complex semantics of events but may also be influenced by news coverage density, linguistic differences, and media attention biases. Generative AI may provide more granular semantic representations of geopolitical risks; however, establishing specialized forecasting and decision-making models tailored to energy projects remains necessary to map this information to the risk exposure and potential future investment losses of specific transnational photovoltaic projects.

In recent years, advances in deep learning and graph representation learning have provided new technical tools for dynamically predicting complex geopolitical events. While traditional recurrent neural networks and temporal convolutional networks can capture the temporal correlations in sequences of risk events, their ability to represent the dynamic interrelationships formed by various types of relationships between nations is relatively limited. Graph neural networks (GNNs) learn structural dependencies between entities through message passing and neighborhood aggregation, providing effective methods for modeling international relations, predicting complex events, and analyzing risk networks. Deng et al. [11] proposed Glean, a multi-event prediction framework based on dynamic knowledge graphs, which integrates event relationships and textual context to predict future events and potential participants. Li et al. [12] proposed RE-GCN, which uses relationship-aware graph convolutions and a recurrent evolution mechanism to capture changes in entities and relationships within temporal knowledge graphs, providing an effective spatiotemporal modeling approach for future event inference. Lim et al. [13] proposed the Temporal Fusion Transformer (TFT), which utilizes variable selection, gating mechanisms, and temporal attention to achieve time-series modeling across multiple variables and multiple prediction time horizons. Although these models can learn complex dynamic relationships, their original research tasks primarily focused on event relationship prediction or general time-series forecasting and may not be directly applicable to the concurrent challenges of country-specific risk variations, project heterogeneity, and investment economic constraints present in transnational photovoltaic projects in Africa. Specifically, when geopolitical risks manifest as sudden events, irregular time intervals, and cross-border interdependencies, relying solely on a single time-series model or a graph model with a fixed adjacency matrix may prove insufficient to simultaneously capture the characteristics of short-term shocks, long-term accumulation, and cross-border propagation of risks.

Generative artificial intelligence, particularly large language models (LLMs), offers a new research paradigm for addressing the automatic understanding and knowledge integration of unstructured geopolitical information. Compared

to traditional text classification models, large language models can process policy announcements, international news, corporate disclosures, and descriptions of historical events within a unified semantic space. By utilizing Retrieval-Augmented Generation (RAG) to retrieve relevant contextual evidence, they provide richer information for risk identification and interpretation. Mouakher et al. [14] proposed the LLM4Geopolitics framework, which combines domain-adapted large language models, knowledge graph retrieval, and time-series Transformers to enable the prediction and interpretable analysis of geopolitical events. Dong et al. [15] proposed GeoDyG-LLM, which fuses representations of international relations extracted by dynamic graph neural networks with large language models via a learnable projection module, and employs a parameter-efficient fine-tuning method to predict cyberattacks between nations. Cen et al. [16] further combined hierarchical semantic extraction from large language models, heterogeneous graph neural networks, and temporal prediction models for event-driven time series forecasting. These studies indicate that integrating textual semantics, dynamic relationship graphs, and deep temporal encoding represents a key direction for complex event prediction; they also indicate that combining retrieval-augmented generation, graph neural networks, and large language models, without task-specific integration, is insufficient to establish a meaningful methodological contribution. The central research question is therefore how to establish a multimodal risk prediction framework for real-world investment scenarios that is supported by reliable evidence, reflects the economic implications of projects, and has clear decision-making objectives.

Although the aforementioned studies have made significant progress, existing methods still face several key challenges in the context of cross-border photovoltaic project investments in Africa. First, there are significant issues regarding semantic heterogeneity and the reliability of evidence in multisource geopolitical risk information. Second, there is a lack of a unified representation mechanism linking the cross-border dynamic interrelationships of geopolitical risks to project-level risk exposure. Third, there are issues regarding credibility, temporal consistency, and interpretability between generative risk information and neural network prediction results. Finally, risk forecasts are not always translated into operational investment decisions.

To address these challenges, this study proposes a framework for predicting geopolitical risks and making intelligent investment decisions for transnational photovoltaic projects in Africa, based on evidence-constrained generative artificial intelligence and spatiotemporal graph neural networks (Evidence-Grounded Graph-LLM Framework for Geopolitical Risk Prediction and Investment Decision-Making, EG-GeoInvest). This framework focuses on African countries and cross-border photovoltaic investment projects. By combining multisource information fusion, dynamic relationship representation, generative semantic understanding, and risk-optimized decision-making, it establishes a unified prediction-to-decision process ranging from the identification of geopo-

litical risk events to the allocation of investment capital. First, the proposed framework integrates ACLED, GDELT, AI-GPR, World Bank governance and macroeconomic indicators, Global Solar Atlas data, and verifiable PV project investment information to the framework establishes a multisource heterogeneous dataset covering political security, policy and regulatory, cross-border economic, financial sovereignty, and social governance risks. By using evidence-constrained generative models to identify event subjects, occurrence times, risk types, and transnational relationships in news reports, and by applying multisource consistency checks and temporal constraints, the system enhances the traceability and reliability of risk characteristics.

II. Multisource Heterogeneous Dataset Construction and Geopolitical Risk Association Modeling

To systematically characterize the geopolitical risks in various African countries and their dynamic impact on cross-border photovoltaic investment projects, this study constructs a multisource, heterogeneous dataset that integrates geopolitical events, semantic information from news articles, cross-border economic linkages, photovoltaic project attributes, and macro-financial indicators. The overall data construction process is shown in Figure 1 and primarily consists of three stages: the construction of the geopolitical risk event dataset, the construction of the news event dataset, and the construction of the multimodal risk association dataset. Unlike traditional assessment methods that rely on static country risk indices, this framework uses dynamic risk relationships between countries as a link to align unstructured news evidence, structured political events, and project-level investment data both temporally and by entity, thereby providing a unified data foundation for subsequent joint modeling using generative AI and spatiotemporal graph neural networks.

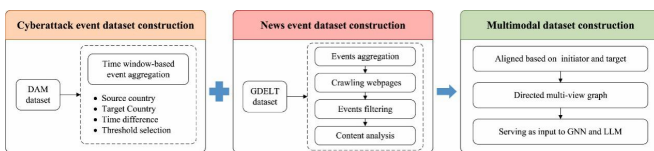


Figure 1: Multisource Geopolitical Risk Events, News Semantics, and Investment Data Fusion Framework

A. Construction of a Dataset on Geopolitical Risk Events in Africa

First, using African countries as the basic units of geographic analysis, we comprehensively utilized the Armed Conflict Location & Event Data (ACLED) [17] and the Global Database of Events, Language, and Tone (GDELT) [18], the World Bank's Worldwide Governance Indicators (WGI), and relevant publicly available government data to collect information on political conflicts, changes in policy regulation, cross-border trade restrictions, sovereign financial risks, and social security incidents in different countries. Given that transnational photovoltaic projects typically involve host

countries, foreign investors, international financial institutions, and equipment-supplying countries, the scope of the study is further expanded to include countries outside Africa that have verifiable investment, trade, or financing relationships with African projects, to ensure the completeness of the risk transmission network.

Let the set of African countries be denoted as $\mathcal{C}_A$, the set of other countries with project investment or economic ties to them as $\mathcal{C}_F$, and the set of PV projects as $\mathcal{P}$. Geopolitical risk events between countries are represented as:

$$e_n = (o_n, d_n, \tau_n, k_n, s_n, \ell_n, \mathbf{v}_n, q_n). \quad (1)$$

Here, o_n and d_n represent the country of origin and the affected country of an event, respectively; for domestic events with no clear transnational implications, we set $d_n = o_n$; τ_n represents the actual time of the event; k_n represents the risk event category; s_n represents the severity of the event; ℓ_n denotes the geographic location of the event; $\mathbf{v}_n$ denotes the semantic features of the event; $q_n \in [0, 1]$ denotes the credibility of the event, which has been verified through evidence and statistically calibrated.

To address the shortcomings of traditional risk statistical methods—which overlook the temporal nature, severity, and national differences of events—this study employs a sliding time window and an exponential decay mechanism to construct a dynamic geopolitical risk representation at the national level:

$$I_{i,t}^{(k)} = \frac{\sum_{e_n \in \mathcal{E}_{i,t}^{(k)}} q_n s_n \omega_{i,n}^{(k)} \exp[-\lambda_k(t - \tau_n)]}{(1 + N_{i,t}^{\text{news}})^{\nu_k}}. \quad (2)$$

Specifically, $\mathcal{E}_{i,t}^{(k)}$ denotes the set of type- k risk events associated with country i within the time window $[t - \Delta, t]$; $\lambda_k > 0$ is the time decay coefficient for different risk types; $\omega_{i,n}^{(k)}$ is the association weight between events and countries; $N_{i,t}^{\text{news}}$ is the news coverage volume for the corresponding country within that time window; and $\nu_k \in [0, 1]$ is the news coverage bias correction parameter. These parameters are determined using training and validation sets to avoid manually specifying uniform risk weights.

Based on the above representation, dynamic risk vectors for each country can be obtained across dimensions such as political security, energy policy, cross-border trade, financial sovereignty, and social governance:

$$\mathbf{R}_{i,t} = [R_{i,t}^{(1)}, R_{i,t}^{(2)}, \dots, R_{i,t}^{(K)}]^\top \in \mathbb{R}^K. \quad (3)$$

This vector preserves the heterogeneity of different types of risk rather than simply aggregating them into a single composite index, thereby providing a basis for identifying the distinct risks faced by different countries and photovoltaic projects.

B. Building News Event Datasets Based on Generative Artificial Intelligence

Second, to capture policy semantics, complex international relations, and potential causal pathways that event databases alone may overlook, this study constructs a multilingual news corpus focused on transnational photovoltaic investments in Africa using GDELT, official government announcements, International Energy Agency reports, and project investment disclosure documents.

The news processing workflow includes event aggregation, web content acquisition, event filtering, and semantic analysis. In this process, generative AI models, combined with Retrieval-Augmented Generation (RAG), perform entity recognition, risk type classification, event relationship extraction, and analysis of investment impact pathways on news texts [16].

For a single risk event covered by multiple news sources, the reports are first clustered according to event actors, geographic location, time of occurrence, and semantic similarity to reduce duplicate counts caused by reprinted reports. Let the set of news articles corresponding to event e_n be denoted as $\mathcal{N}_n$; its semantic fusion representation is defined as:

$$\mathbf{z}_n = \sum_{m \in \mathcal{N}_n} \alpha_{m,n} \phi_{\text{LLM}}(x_m, \mathcal{K}_{\leq t}),$$

$$\alpha_{m,n} = \frac{\exp(\mathbf{a}^\top \tanh(\mathbf{W}_h \mathbf{h}_m + \mathbf{b}_h) + \log(r_m + \varepsilon))}{\sum_{j \in \mathcal{N}_n} \exp(\mathbf{a}^\top \tanh(\mathbf{W}_h \mathbf{h}_j + \mathbf{b}_h) + \log(r_j + \varepsilon))}, \quad (4)$$

where $\phi_{\text{LLM}}(\cdot)$ denotes the semantic encoding function based on a generative pre-trained model; x_m is the (m)th news article; $\mathcal{K}_{\leq t}$ denotes the external knowledge available by decision time t ; $\mathbf{h}_m$ is the news encoding feature; r_m is the reliability weight obtained from source quality assessment; $\alpha_{m,n}$ is the learnable news attention coefficient; $\mathbf{W}_h$, $\mathbf{a}$, and $\mathbf{b}_h$ are parameters to be trained.

To reduce factual hallucinations and unsupported event attributions generated by language models, this study further introduces a multisource evidence consistency check and defines an event credibility estimation function:

$$\sigma = [\beta_0 + \beta_1 C_n^{\text{src}} + \beta_2 C_n^{\text{ent}} + \beta_3 \log(1 + M_n^{\text{ind}}) - \beta_4 D_n^{\text{contra}}], \quad (5)$$

where C_n^{src} represents source credibility; C_n^{ent} represents the degree of evidence supporting key information such as the subject, time, and location of the event; M_n^{ind} is the number of independent pieces of evidence after removing reposts and shared original sources; D_n^{contra} represents the degree of conflict among different pieces of evidence; $\sigma(\cdot)$ denotes the sigmoid function. The model's output requires further probabilistic calibration using a manually verified set of events to avoid interpreting the large language model's own subjective confidence scores directly as the probability of an event occurring.

Through the aforementioned mechanisms, news texts are converted into structured event records featuring uniform

country identifiers, timestamps, risk categories, semantic representations, and evidence credibility, thereby achieving an effective linkage between the semantic information generated by generative AI and geopolitical risk data.

C. Multimodal Data Fusion and Directed Heterogeneous Graph Construction

After completing the construction of the dataset on geopolitical risk events and news events, we further incorporated data from the World Bank's Private Participation in Infrastructure (PPI) database [19], the Global Solar Atlas, the International Energy Agency, and relevant project investment disclosure materials to collect data on photovoltaic projects across African countries, including installed capacity, construction phase, investment scale, foreign investors, capital costs, solar resource conditions, and project financing structures. At the same time, we integrated data on exchange rates, inflation, the quality of government governance, international trade, and cross-border financing relationships to form a multi-level, interconnected dataset spanning the country-project-time dimensions [19].

Since the geopolitical risks faced by cross-border photovoltaic projects depend not only on the political and economic conditions of the host country but are also influenced by risk changes in the countries of origin for equipment imports, investors' home countries, and financing sources, this study models the aforementioned multisource data as a dynamic directed heterogeneous graph:

$$\mathcal{G}_t = (\mathcal{V}_C \cup \mathcal{V}_P \cup \mathcal{V}_I, \{\mathcal{E}_t^{(r)}\}_{r=1}^R, \mathbf{X}_t, \mathbf{A}_t). \quad (6)$$

In this context, $\mathcal{V}_C$, $\mathcal{V}_P$, and $\mathcal{V}_I$ represent the sets of nodes for countries, photovoltaic projects, and investment or financing entities, respectively; $\mathcal{E}_t^{(r)}$ represents the r th type of relationship edge, including inter-country trade, project ownership, financing links, equipment supply, and cross-border energy infrastructure links; $\mathbf{X}_t$ denotes multimodal node features; $\mathbf{A}_t$ is the relationship adjacency matrix that evolves over time.

To simultaneously reflect the intensity of cross-border economic interdependence and the dynamic changes in geopolitical risks, we define the directed association weight from country (j) to country (i) under the r th type of relationship as:

$$\alpha_{ji,t}^{(r)} = \frac{M_{ji,t}^{(r)} \exp[\mathbf{w}_r^\top \tanh(\mathbf{W}_r [\mathbf{R}_{j,t} \parallel \mathbf{R}_{i,t} \parallel \mathbf{z}_{ji,t}]) + \gamma_r \log(1 + \rho_{ji,t}^{(r)})]}{\sum_{v \in \mathcal{C}} M_{vi,t}^{(r)} \exp[\mathbf{w}_r^\top \tanh(\mathbf{W}_r [\mathbf{R}_{v,t} \parallel \mathbf{R}_{i,t} \parallel \mathbf{z}_{vi,t}]) + \gamma_r \log(1 + \rho_{vi,t}^{(r)})]},$$

$$j \in \mathcal{C}, \quad r = 1, \dots, R \quad (7)$$

where $M_{ji,t}^{(r)} \in \{0, 1\}$ represents the relationship mask for real economic or project ties; $\rho_{ji,t}^{(r)}$ represents the strength of observable trade, investment, or financing ties; $\mathbf{z}_{ji,t}$ represents

the semantic representation of news event relationships between countries; $\parallel$ denotes vector concatenation; $\mathbf{W}_r, \mathbf{w}_r^\top$, and γ_r are relationship-specific learnable parameters. By normalizing each relationship category separately, the model can describe the strength of risk associations between different countries while preserving the directionality of the network. For nodes without observed relationship edges, the model additionally retains self-loops to ensure that their local risk information can participate in subsequent updates.

Further considering the actual associations between photovoltaic projects and multiple countries, we define the project-country exposure matrix:

$$\beta_{pi,t} = \frac{m_{pi,t} \exp(\boldsymbol{\eta}^\top \mathbf{u}_{pi,t})}{\sum_{j \in \mathcal{C}} m_{pj,t} \exp(\boldsymbol{\eta}^\top \mathbf{u}_{pj,t})}, \quad i \in \mathcal{C}. \quad (8)$$

In this context, $m_{pi,t}$ indicates whether project (p) has a verified host country, investment, financing, equipment supply, or electricity trade link with country (i); $\mathbf{u}_{pi,t}$ is the attribute vector for the corresponding link, including investment origin, equipment procurement dependencies, financing exposure, and host country attributes; and $\boldsymbol{\eta}$ represents the parameters to be learned. Each project has at least one host country relationship to ensure that the denominator is non-zero. For cross-border relationships that cannot be confirmed, they are not directly treated as definite zero exposure but are instead recorded separately as missing data.

Based on the aforementioned country risk characteristics and transnational relationship structures, a relationship-aware graph neural network is employed to propagate risk information:

$$\text{LayerNorm} = [\mathbf{h}_{i,t}^{(l)} + \sigma(\sum_{r=1}^R \sum_{j \in \mathcal{N}_i^{(r)}} A_{ji,t}^{(r)} \mathbf{W}_r^{(l)} \mathbf{h}_{j,t}^{(l)} + \mathbf{W}_0^{(l)} \mathbf{h}_{i,t}^{(l)})] \quad (9)$$

where $\mathbf{h}_{i,t}^{(l)}$ represents the risk representation of country (i) at layer (l); $\mathcal{N}_i^{(r)}$ denotes the set of neighboring nodes connected to it via relationship type (r); $\mathbf{W}_r^{(l)}$ and $\mathbf{W}_0^{(l)}$ are the relationship-specific and self-node transformation matrices, respectively. The initial node representation is encoded using a combination of the country's dynamic risk vector, news semantic embeddings, macroeconomic indicators, and a missing data mask.

Finally, the country representation after cross-border risk propagation is fused with the project's own photovoltaic resources, investment scale, construction progress, and financial characteristics to construct a project-level dynamic risk representation using a time-series encoder:

$$\mathbf{z}_{p,t} = \text{TFT}_\theta \left[\sum_{i \in \mathcal{C}} B_{pi,\tau} \mathbf{h}_{i,\tau}^{(L)} \parallel \mathbf{x}_{p,\tau}^{\text{PV}} \parallel \mathbf{x}_{p,\tau}^{\text{fin}} \parallel \mathbf{m}_{p,\tau} \right]_{\tau=t-H+1}^t, \quad (\hat{P}_{p,t+h}^{\text{delay}}, \hat{F}_{p,t+h}^{\text{loss}}) = f_\phi(\mathbf{z}_{p,t}). \quad (10)$$

where TFT_θ denotes the Temporal Fusion Transformer; $\mathbf{x}_{p,\tau}^{\text{PV}}$ and $\mathbf{x}_{p,\tau}^{\text{fin}}$ represent the project's photovoltaic technical attributes and financial attributes, respectively; $\mathbf{m}_{p,\tau}$ is the information-missingness and observability mask; (H) is the length of the historical observation window; (h) is the forecast time horizon; $\hat{P}_{p,t+h}^{\text{delay}}$ is the probability of a major project delay in the future; and $\hat{F}_{p,t+h}^{\text{loss}}$ is the predicted distribution of project economic losses. Project delay labels are constructed based on recorded planned and actual milestone dates. Projects for which subsequent outcomes are missing or that have not yet reached the observation endpoint are treated as missing values rather than being directly classified as risk-free projects.

To ensure that the above dynamic dataset supports effective historical backtesting, the availability of all features is determined by the date on which the information became publicly available, rather than solely by the time the event occurred. Let:

$$f_\Theta = (\mathcal{F}_t). \quad (11)$$

Here, t_n^{release} denotes the time when information first becomes available, and $\mathcal{F}_t$ denotes the set of information available up to the decision time (t). This design avoids forward-looking bias caused by the inclusion of backfilled historical news, revisions to the event database, and project completion information entering the model prematurely.

III. Geopolitical Risk Exposure and Spatial Interdependence of Cross-Border Photovoltaic Investments

Investment risks in transnational photovoltaic projects in Africa depend not only on the host country's political stability, energy policies, and economic environment, but are also jointly influenced by regional electricity trade, reliance on cross-border infrastructure, and geopolitical relations among nations. Given the significant differences among African countries with respect to energy resource endowments, electricity demand, infrastructure development levels, and institutional environments, cross-border energy networks have formed a complex spatial interdependence structure, making it possible for localized geopolitical shocks to spread to other countries and projects through energy trade, investment linkages, and supply chain relationships [3]. To reveal the relationship between the layout of transnational energy infrastructure and geopolitical risks, Figure 2 illustrates the spatial configuration characteristics of Africa's cross-border electricity transmission networks under different political-risk constraints. Building on this, this study establishes a dynamic risk-association modeling framework for transnational photovoltaic investments in Africa.

The gray nodes in Figure 2 represent country location nodes used for network visualization, while the black directed edges indicate the direction of electricity transmission between countries; the width of the edges corresponds to the annual volume of cross-border electricity transmission (TWh/year). Figure 2(A) shows a 2030 cross-border power transmission network scenario for Africa that aims to minimize the total cost of the energy system, while Figure 2(B) shows an optimized scenario that incorporates political risk constraints, with the upper limit of the avoidable political risk index set at 10 in the original study. Both scenarios are derived from an energy system planning model and do not represent an observed or constructed 2030 transmission network.

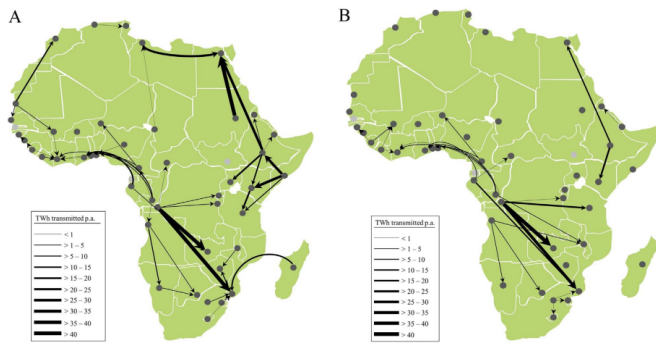


Figure 2: Spatial configurations of the African cross-border electricity transmission network under different political-risk constraints and implications for photovoltaic investment risk modeling. (A) Cost-minimization scenario for 2030; (B) Political-risk-constrained scenario for 2030 (maximum preventable political risk index of 10). Arrow directions indicate electricity transmission flows, and line widths represent annual electricity transmission volumes. Original network maps reproduced from Trotter et al. [3]

From a spatial perspective, Figure 2(A) reveals substantial reliance on cross-border electricity trade. A large number of energy transmission relationships are concentrated in Central, Eastern, and Southern Africa, with some countries connecting multiple demand markets through large-scale cross-border electricity exports, forming an energy supply network characterized by distinct directionality and imbalance. This configuration allows for the full utilization of different countries' resource endowments and economies of scale, but it also means that some electricity-consuming countries have become highly dependent on a small number of energy-exporting countries. When key exporting countries experience political conflicts, institutional adjustments, disruptions in cross-border trade, or infrastructure operational failures, the resulting shocks may propagate along existing power transmission routes, thereby increasing uncertainty in energy supply and further impacting related transnational energy investment projects.

In contrast, Figure 2(B) shows that, after introducing political risk constraints, the number of cross-border power connections decreases significantly, some of the original large-

scale power transmission relationships are weakened, and the network as a whole exhibits a shift from centralized cross-border energy supply toward a more localized power generation configuration. Previous research indicates that this change is primarily achieved by reducing large-scale power imports from countries with high political risk and increasing domestic renewable energy generation—particularly solar photovoltaic power generation—in each country. This suggests that cross-border energy allocation focused solely on minimizing system costs may not necessarily minimize political risk. Instead, enhancing local PV generation capacity and optimizing the structure of energy trade dependencies may serve as key strategies for reducing geopolitical risks in cross-border energy systems. However, localized generation does not eliminate all investment risks; host-country risks—such as land tenure systems, financing costs, government creditworthiness, and project regulation—may still persist.

These differences between network scenarios inform the construction of a model for the propagation of geopolitical risks in transnational photovoltaic investment in Africa. Unlike traditional methods that rely solely on national political risk indices to assess the investment environment, this study further considers energy trade links between countries as potential channels for cross-border risk propagation. By integrating geopolitical events, semantic representations of generative AI news, and project-investment relationships—as established in the previous section—this study constructs a multilayer directed heterogeneous network encompassing energy transmission, international investment, equipment supply, and cross-border financing. Let the cross-border electricity transmission volume from country (j) to country (i) be denoted as $F_{ji,t}$. Then, the relative dependence weight of country (i) on external electricity supplier (j) is expressed as:

$$\beta_{ji,t}^E = \frac{M_{ji,t}^E F_{ji,t}}{\varepsilon + \sum_{k \in \mathcal{C}} M_{ki,t}^E F_{ki,t}}, \quad j \in \mathcal{C}, \quad (12)$$

where $M_{ji,t}^E$ indicates whether there is an electricity transmission link between country (j) and country (i), $\mathcal{C}$ denotes the set of countries included in the study, and ε is a small constant used to prevent the denominator from becoming zero. When a country has no cross-border electricity imports, its corresponding external electricity dependence weight is zero. This indicator characterizes only the relative exposure of identified cross-border electricity links and is not directly equivalent to a country's overall geopolitical risk level. For other types of cross-border investment, supply chain, and financing links, corresponding relationship matrices are constructed based on equity relationships, procurement dependence, and financing exposure, respectively.

To further account for the heterogeneous propagation characteristics of different geopolitical risks within a national network, we combine cross-border relationship weights, national risk vectors, and project exposure to define the network-

associated risk of a photovoltaic project (p) at time (t) as follows:

$$\sum_{i \in \mathcal{C}} B_{pi,t} = \left[\omega_0^\top \mathbf{R}_{i,t} + \sum_{r \in \mathcal{T}} \lambda_r \sum_{j \in \mathcal{N}_i^{(r)}} A_{ji,t}^{(r)} \omega_r^\top \mathbf{R}_{j,t} \right], \quad (13)$$

where $B_{pi,t}$ represents the exposure of project (p) to country (i); $\mathbf{R}_{i,t}$ and $\mathbf{R}_{j,t}$ represent the dynamic geopolitical risk features derived from multisource risk events and generative artificial intelligence, respectively; $\mathcal{T}$ is the set of cross-border relationship types, including electricity trade, supply chain, investment, and financing relationships; $A_{ji,t}^{(r)}$ represents the directed association weight for the r th type of relationship; ω_0 , ω_r , and λ_r are parameters to be learned. This model simultaneously captures the extent of a project's direct exposure to risks in its host country, as well as the indirect effects of risks from other countries arising through cross-border economic linkages.

Building on this foundation, this study further employs a combination of relationship-aware graph neural networks and time-series encoders to learn the spatial correlations and temporal evolution of cross-border geopolitical risks, dynamically adjusting the importance of different countries and cross-border relationships through a graph attention mechanism. At the same time, events such as political conflicts, policy adjustments, international sanctions, and trade restrictions—extracted by generative artificial intelligence—are used as dynamic semantic inputs to enhance the model's ability to identify and respond to sudden geopolitical shocks. For projects with a high degree of reliance on cross-border electricity trade, the analysis focuses on depicting risks associated with energy supply disruptions and electricity sales; for local photovoltaic projects that depend on foreign investors, overseas equipment supplies, or international financing, the study models the risk exposures arising from capital flows, supply chain disruptions, and changes in financing costs, respectively, thereby avoiding the simplistic equating of energy trade networks with project investment networks [3], [5].

Finally, by integrating dynamic network risk representations with attributes such as the installed capacity of photovoltaic projects, solar irradiance resources, investment costs, financing structures, and construction phases, we predict project-delay probabilities, cash flow losses, and risk-adjusted net present value under geopolitical shocks, and incorporate the resulting risk probability distributions into Conditional Value-at-Risk (CVaR) and distribution-robust investment optimization models. Conditional Value-at-Risk (CVaR) provides an established framework for assessing portfolio tail losses [20]. By establishing investment scenarios such as cost-priority, risk-constrained, and risk-return-balanced approaches, we compare differences across countries and project portfolios with respect to investment returns, tail losses, and cross-border risk exposure to test whether generative artificial intelligence and spatiotemporal graph neural networks can provide decision-making insights that go beyond traditional

static risk metrics.

It should be noted that the 2030 power transmission scale shown in Figure 2 is based on scenario simulations from existing studies; its purpose is to illustrate the relationship between energy network structure and political risk, and it cannot be directly used as actual power flow data from the historical sample in this study. Therefore, in subsequent empirical studies, a dynamic network should be reconstructed using verifiable data on cross-border power trade, project investment, and financing relationships during the study period, and the predictive contributions of different types of relationships should be tested separately.

IV. Geopolitical Risk Forecasting and a Framework for Intelligent Investment Decision-Making

To address issues in identifying geopolitical risks for cross-border photovoltaic projects in Africa—such as the heterogeneity of information from multiple sources, complex cross-border relationships, the difficulty of modeling dynamic risk evolution, and the lack of interpretability in traditional predictive models—this study proposes a framework for geopolitical risk prediction and intelligent investment decision-making that integrates evidence-grounded graph neural networks with generative large language models (Evidence-Grounded Graph-LLM Framework for Geopolitical Risk Prediction and Investment Decision-Making, EG-GeoInvest).

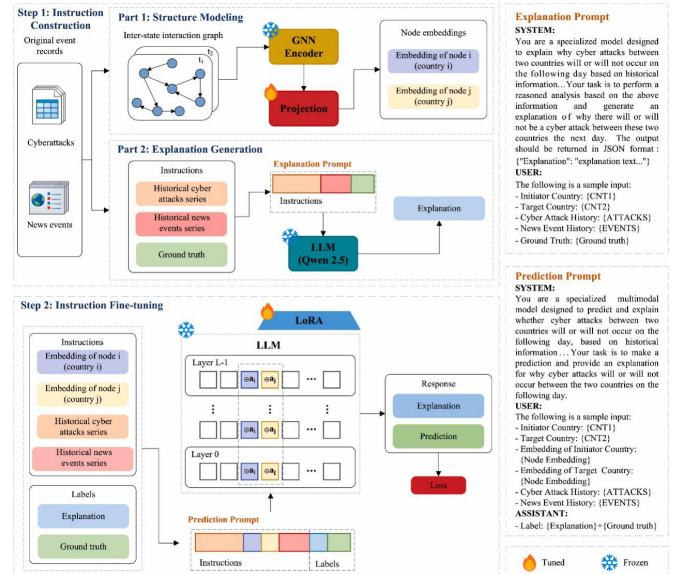


Figure 3: Framework for Geopolitical Risk Prediction and Investment Decision-Making for Transnational Photovoltaic Projects in Africa

As shown in Figure 3, the proposed framework employs a two-stage collaborative training mechanism: the first stage involves risk structure modeling and explanation instruction construction, while the second stage involves risk-oriented, parameter-efficient instruction fine-tuning. By using graph neural networks to capture dynamic geopolitical risk corre-

lations among African countries, this approach employs generative AI to extract semantic information from news events and construct evidence-constrained risk explanations. It then integrates structured graph representations with the semantic space of large language models through a learnable projection module and Low-Rank Adaptation (LoRA) technology [21].

Rather than relying on subjective assessments generated directly by large language models, this study organizes geopolitical risk identification, risk probability prediction, project economic loss estimation, and investment decision optimization into an interconnected modeling process. This enables the model not only to identify potential geopolitical risks facing specific countries and PV projects but also to predict the likelihood of risk events, explain the primary basis for risk formation, and convert the prediction results into quantitative decision-making information that can be used for investment allocation.

A. Modeling the Structure of Transnational Geopolitical Risks and Representation Learning

In the first phase, using the multisource heterogeneous dataset described above, we establish a dynamic, heterogeneous relationship network comprising African countries, transnational photovoltaic projects, investors, and financing institutions. Unlike the original framework, which primarily modeled cyberattack relationships between countries, this study focuses on describing various risk-related relationships, including political and security incidents, energy trade, international investment, equipment supply, and project financing.

Let the dynamic, heterogeneous graph corresponding to time window t be:

$$\mathcal{G}_t = (\mathcal{V}, \{\mathcal{E}_t^{(r)}\}_{r=1}^R, \mathbf{X}_t, \mathbf{A}_t, \mathbf{Q}_t), \quad t = 1, \dots, T. \quad (14)$$

In this model, $\mathcal{V} = \mathcal{V}_C \cup \mathcal{V}_P \cup \mathcal{V}_I$ represents the sets of nodes for countries, photovoltaic projects, and investment and financing entities, respectively; $\mathcal{E}_t^{(r)}$ represents the r th type of transnational relationship; $\mathbf{X}_t$ represents the multimodal attributes of nodes; $\mathbf{A}_t$ is the directed association matrix; and $\mathbf{Q}_t$ is the matrix of source evidence credibility and relationship observation status.

Given that different types of transnational relationships play significantly different roles in the propagation of geopolitical risks, this study employs a dynamic graph neural network encoder with a relationship-aware mechanism to learn the dynamic representations of each node through relationship-specific graph attention aggregation.

For a relationship of type (r) between node (i) and node (j) , define its time-aware attention coefficient as follows:

$$\gamma_r = \Delta\tau_{ki,t} + \zeta_r q_{ki,t}^{(r)}, \quad (15)$$

where $\mathbf{h}_{i,t}^{(l)}$ represents the node representation at layer (l) ; $\mathbf{e}_{ji,t}^{(r)}$ represents edge attributes; $\rho_{ji,t}^{(r)}$ denotes the strength of actual investment, trade, or financing ties; $\Delta\tau_{ji,t}$ is the time interval between the relationship-related event and the current

time window; $q_{ji,t}^{(r)}$ is the reliability of verified relationship evidence; (d) is the attention feature dimension.

By jointly modeling economic-link strength, event recency, and source reliability, this mechanism enables the model to adaptively identify potential risk transmission pathways based on the actual interconnections among different countries, rather than relying on fixed spatial adjacencies or manually set risk propagation weights.

Subsequently, by employing residual-based relationship graph aggregation and a gated loop mechanism, the model achieves joint encoding of transnational risk structural characteristics and historical evolution information:

$$\mathbf{h}_{i,t}^{(l+1)} = \text{LayerNorm}[\mathbf{h}_{i,t}^{(l)} + \sigma(\sum_{r=1}^R \sum_{j \in \mathcal{N}_i^{(r)}} \alpha_{ji,t}^{(r,l)} \mathbf{W}_r^{(l)} \mathbf{h}_{j,t}^{(l)} + \mathbf{W}_0^{(l)} \mathbf{h}_{i,t}^{(l)})], \quad (16)$$

$$\mathbf{g}_{i,t} = \text{GRU}(\mathbf{h}_{i,t}^{(L)}, \mathbf{g}_{i,t-1}), \quad (17)$$

$$l = 0, \dots, L-1, \quad (18)$$

where $\mathbf{g}_{i,t}$ represents the node risk representation after incorporating historical dynamic information. For transnational photovoltaic projects in Africa, this representation includes not only the political and economic environment of the host country but also captures the potential indirect risk impacts arising from other countries through actual investment, equipment supply, and financing channels.

At this stage, the graph neural network encoder employs pre-trained parameters based on historical geopolitical events and remains frozen during the subsequent cross-modal alignment process to reduce the need for large-scale parameter updates given the limited number of project labels.

B. Cross-Modal Semantic Alignment

Since the structural vectors output by graph neural networks differ from the token representations of large language models with respect to both dimensionality and semantic space, this study introduces a learnable nonlinear projection module to map the representations of country and project nodes into continuous soft prompts that can be directly processed by large language models.

For investment relationships involving the source country (o), the host country (d), and the photovoltaic project (p), we define a joint structural representation:

$$\mathbf{c}_{p,t} = [\mathbf{g}_{o,t} \parallel \mathbf{g}_{d,t} \parallel \mathbf{g}_{p,t} \parallel \sum_{i \in C} B_{pi,t} \mathbf{g}_{i,t}], \quad p \in \mathcal{P}, \quad (19)$$

where $B_{pi,t}$ denotes the project-country risk exposure coefficient established earlier, and $\parallel$ denotes feature concatenation.

C. Generating Risk Interpretations and Constructing Instructions

To ensure that generative models not only possess risk prediction capabilities but can also provide explanations for investment risks that align with historical evidence, this study

constructs a dataset of risk explanation prompts tailored to African photovoltaic projects.

Specifically, the explanation prompts from the original dataset—which dealt with cyberattacks between nations—were adapted for the task of explaining geopolitical risks in PV investments. Each prompt includes the project host country, the source country of investment, a sequence of historical risk events, semantic evidence from news reports, cross-border risk correlations, and basic project attributes. The model is then tasked with explaining why the probability of a specific risk event occurring is high or low given the provided information.

At the same time, based on specific investment scenarios, the explanation task is further categorized into political and security risks, changes in energy policy, cross-border supply chain disruptions, financial sovereignty risks, and project construction delays, enabling the model to learn the potential impact pathways of different risk factors on PV investment projects.

Let the set of available information up to the decision time (t) be denoted as $\mathcal{F}_t$, and the verified risk labels for the next (h) periods be denoted as $y_{p,t+h}^{(k)}$. Then, the candidate risk explanations during the training phase can be expressed as:

$$\mathcal{M}_T = (\mathcal{P}_{\text{exp}}[\mathcal{F}_t, \mathbf{Z}_{p,t}^G, y_{p,t+h}^{(k)}]). \quad (20)$$

In this context, $\mathcal{M}_T$ denotes the frozen teacher generative language model, and $\mathcal{P}_{\text{exp}}$ denotes the explanation instruction template. Historical result labels are used solely for offline training supervision and cannot be used as input during the actual prediction phase.

D. LoRA Joint Fine-Tuning for Predicting and Explaining Geopolitical Risks

After completing cross-modal alignment, this study further conducts fine-tuning for risk prediction, enabling the model to predict future risks based on historical geopolitical events and transnational structural information, while simultaneously generating explanations consistent with the basis of the predictions.

At this stage, the graph neural network encoder and the previously trained projection module remain frozen. The attention projection parameters in the language model are updated primarily via LoRA [21] to control training costs and reduce the risk of overfitting with limited samples.

For the linear transformation matrix $\mathbf{W}_0$ in the base large language model, a low-rank update is applied:

$$\Delta \mathbf{W} = \frac{\alpha}{r} \mathbf{B} \mathbf{A}, \quad (21)$$

where $\mathbf{A} \in \mathbb{R}^{r \times d_{\text{in}}}$, $\mathbf{B} \in \mathbb{R}^{d_{\text{out}} \times r}$, $r \ll \min(d_{\text{in}}, d_{\text{out}})$ represent the low-rank dimensions, and α is the scaling parameter. During training, only the low-rank matrix and the task prediction head parameters are updated, while the base model weights remain unchanged.

Regarding the design of prediction instructions, the host country of the project, the source country of investment,

historical geopolitical risk events, semantic information from news articles, and the corresponding graph node embeddings are input into the language model, which is tasked with outputting risk probabilities and structured explanations for a specified future time range. Unlike the binary prediction for cyberattacks on the following day in the original paper, this study adopts multiple investment decision time windows $h \in \{1, 3, 6\}$ months to better align with the investment decision cycle of cross-border photovoltaic projects.

The input to the multimodal model is defined as:

$$\mathbf{Z}_{p,t}^F = \text{Concat}(\text{Embed}(\mathcal{P}_{\text{pred}}, \mathcal{T}_{p,\leq t}), \mathbf{Z}_{p,t}^G), \quad (22)$$

where $\mathcal{P}_{\text{pred}}$ denotes the risk prediction task instruction, and $\mathcal{T}_{p,\leq t}$ represents the sequence of news events, project attributes, and historical risk data prior to the prediction time step. Graph-structured soft prompts are inserted into the text embedding sequence at predefined positions and are jointly encoded by a LoRA-adapted Transformer.

Task-relevant fused representations are further extracted:

$$\mathbf{Z}_{p,t}^{\text{LLM}} = \text{AttnPool}[\text{LLM}_{\theta_0 + \Delta\theta}(\mathbf{H}_{p,t}^{(0)})]. \quad (23)$$

This representation, which incorporates historical text semantics, transnational graph structures, and photovoltaic project characteristics, is fed into the risk prediction head and the risk explanation decoder, enabling collaborative modeling for the prediction of geopolitical risk probabilities and the generation of explanations.

V. Extraction of Dynamic Risk Characteristics

To effectively capture the temporal evolution of geopolitical risks and the complex spatial dependencies among countries in transnational photovoltaic investments in Africa, this study designs a Spatiotemporal Geopolitical Risk Encoding Module (ST-GREM) within the proposed EG-GeoInvest framework, which integrates a Temporal Convolutional Network (TCN) with a Graph Convolutional Network (GCN). As illustrated in Figure 4, by alternately stacking TCN and GCN layers, this module enables multiscale temporal feature extraction of geopolitical events, the propagation of transnational risk correlations, and the prediction of future risk states, thereby providing structured spatiotemporal representations for subsequent multimodal risk inference and intelligent investment decision-making by generative large language models.

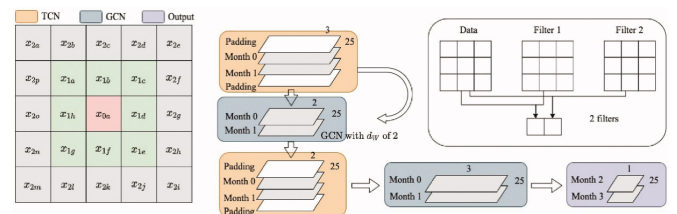


Figure 4: Illustrative Spatiotemporal Geopolitical Risk Encoding Module with Alternating Temporal and Graph Convolutional Layers

Specifically, the orange modules in Figure 4 represent temporal convolution operations, the blue modules represent graph convolution operations, and the purple modules represent future risk prediction outputs. The matrix on the left represents the spatial arrangement of nodes representing different countries and their historical risk characteristics; the central section illustrates the spatiotemporal information propagation process as TCN and GCN alternate; and the right side shows how convolution filters aggregate local features. The 25 illustrative nodes, adjacent months, and number of filters shown in the figure are used solely to illustrate the network's computational structure; the actual number of nodes in the study is determined jointly by African countries and other countries with cross-border investment ties.

A. Extraction of Multiscale Geopolitical Risk Evolution Characteristics

Because geopolitical risks may be persistent, abrupt, or concentrated within particular periods, this study first employs TCN to capture the nonlinear temporal dependencies among historical risk events. For country node (i), we fuse the semantic information of news events extracted by generative AI, the intensity of political and security events, changes in energy policy, cross-border trade relations, and macro-financial risk indicators to form a historical dynamic risk feature sequence $\mathbf{X}_{i,t} = \mathbf{x}_{i,t-H+1}, \dots, \mathbf{x}_{i,t}$, where (H) denotes the length of the historical observation window.

By employing Dilated Causal Convolution with causal constraints and a gated activation mechanism, risk evolution patterns across different time scales are extracted without introducing future information:

$$\begin{aligned} \mathbf{U}_{i,t}^{(l)} = & \tanh\left(\sum_{k=0}^{K-1} \mathbf{W}_{f,k}^{(l)} \mathbf{H}_{i,t-kd_l}^{(l)} + \mathbf{b}_f^{(l)}\right) \\ & \odot \sigma\left(\sum_{k=0}^{K-1} \mathbf{W}_{g,k}^{(l)} \mathbf{H}_{i,t-kd_l}^{(l)} + \mathbf{b}_g^{(l)}\right), \end{aligned} \quad (24)$$

$$d_l = 2^{l-1},$$

where $\mathbf{H}_{i,t}^{(l)}$ represents the input features of layer (l); $\mathbf{U}_{i,t}^{(l)}$ represents the temporal convolution output; (K) denotes the size of the convolution kernel; d_l denotes the dilation factor; $\mathbf{W}_{f,k}^{(l)}$ and $\mathbf{W}_{g,k}^{(l)}$ are the parameters for feature transformation and gated convolution, respectively; $\odot$ denotes element-wise multiplication.

Through dilated convolutions, the model can expand the temporal receptive field within a finite network depth while capturing the dynamic dependencies between short-term events—such as political conflicts and policy adjustments—and long-term institutional risks. Causal padding is used to maintain consistency across the temporal dimension, ensuring that the risk representation at any given time depends only on information from that time step and earlier, thereby preventing future data leakage.

B. Modeling the Propagation of Transnational Geopolitical Risks

Since transnational photovoltaic projects in Africa typically involve energy trade, investment cooperation, equipment supply, and international financing relationships among multiple countries, simple time-series models struggle to capture the interconnected effects of geopolitical shocks within national networks. Therefore, this study further uses a relationship-aware GCN to perform spatial propagation and aggregation of the risk features generated by the TCN.

Based on the multilayer directed heterogeneous graph $\mathcal{G}_t$ constructed in the preceding section, and taking into comprehensive consideration the directed association weights formed by cross-border electricity trade, investment relationships, financing links, and historical risk events among countries, we define the transnational risk graph convolution operation as follows:

$$\begin{aligned} \mathbf{U}_{i,t}^{(l+1)} = & \sigma[\mathbf{W}_0^{(l)} \mathbf{U}_{i,t}^{(l)} \\ & + \sum_{r=1}^R \sum_{j \in \mathcal{N}_i^{(r)}} \frac{A_{ji,t}^{(r)}}{\sqrt{(D_{i,t}^{(r)} + \varepsilon)(D_{j,t}^{(r)} + \varepsilon)}} \mathbf{W}_r^{(l)} \mathbf{U}_{j,t}^{(l)}], \\ & l = 0, \dots, L-1. \end{aligned} \quad (25)$$

In this context, $\mathbf{U}_{j,t}^{(l)}$ represents the node representation after cross-national graph convolution; $A_{ji,t}^{(r)}$ is the directed risk association weight from country (j) to country (i) under the r th type of cross-border relationship; $D_{i,t}^{(r)}$ and $D_{j,t}^{(r)}$ represent the weighted in-degree and out-degree, respectively, of the corresponding nodes in this relationship network; $\mathbf{W}_r^{(l)}$ is a relationship-specific learnable parameter; and $\mathcal{N}_i^{(r)}$ denotes the set of neighboring nodes with verifiable cross-border connections.

Through the above mechanism, the model can adaptively aggregate country risk information with different economic dependency characteristics while preserving the directionality of cross-border relationships. For example, even if a photovoltaic project is located in a country with a relatively stable political environment, it may still face indirect risk exposure due to heavy reliance on equipment supplies from other countries, cross-border electricity markets, or international financing. GCNs can capture such structural associations through directed relationship aggregation, providing information for project-level geopolitical risk assessment that goes beyond static risk indicators of the host country.

C. Alternating Stacking of TCN and GCN with Integration of Spatiotemporal Risk Representations

To jointly model the temporal dynamics of risk events and their spatial correlations across countries, this study adopts an alternating stacked TCN–GCN architecture. In each spatiotemporal encoding unit, historical risk evolution features are first extracted using TCN, followed by the aggregation of cross-national relationship information via GCN. The resulting spatial features are then fed into the next layer of tem-

poral convolutional units, enabling layer-by-layer interaction between spatiotemporal features.

Considering that multilayer graph convolutions may lead to excessive smoothing of node representations, while deep temporal convolutions may suffer from feature decay, this study introduces residual connections and a gated fusion mechanism:

$$\mathbf{Z}_{i,t}^{(l)} = \sigma(\mathbf{W}_z^{(l)}[\mathbf{U}_{i,t}^{(l)} \parallel \mathbf{U}_{i,t}^{(l)}] + \mathbf{b}_z^{(l)}), \quad (26)$$

$$\begin{aligned} \mathbf{H}_{i,t}^{(l+1)} = & \text{LayerNorm}[\mathbf{W}_{\text{res}}^{(l)} \mathbf{H}_{i,t}^{(l)} \\ & + \mathbf{Z}_{i,t}^{(l)} \odot \mathbf{U}_{i,t}^{(l)} \\ & + (\mathbf{1} - \mathbf{Z}_{i,t}^{(l)}) \odot \mathbf{U}_{i,t}^{(l)}], \quad (27) \\ & l = 0, \dots, L-1, \end{aligned}$$

where $\mathbf{Z}_{i,t}^{(l)}$ is the spatiotemporal feature fusion gating vector; $\mathbf{W}_{\text{res}}^{(l)}$ is the residual projection matrix used for dimensionality matching; and $\text{LayerNorm}(\cdot)$ is used to stabilize the feature distribution.

This design enables the model to dynamically adjust the relative contributions of local historical risks and transnational propagation risks. When a country's risk is primarily driven by internal policy changes or political conflicts, the network can retain more of the local temporal features extracted by the TCN; when risks propagate to other countries through cross-border trade, supply chains, or investment relationships, the model can enhance the spatial correlation information output by the GCN.

As the multilayer TCN–GCN modules are executed alternately, country node representations gradually integrate multi-timescale geopolitical event information with multi-order transnational network associations, thereby forming deep spatiotemporal features for subsequent risk prediction.

VI. Experiments and Results

A. Dataset Description and Construction

1) Study Area and Country Selection

This study focuses on African countries, establishing a regional geopolitical risk database covering North Africa, West Africa, East Africa, Central Africa, and Southern Africa, and further incorporating countries outside Africa that have verifiable investment, trade, or financing ties to African photovoltaic projects.

In terms of research design, the study first identifies the 54 sovereign states in Africa as the candidate country set, then screens for valid samples for different experimental tasks based on data coverage, the completeness of project records, and observable cross-border relationships.

To illustrate the intended spatial heterogeneity analysis, Table 1 identifies candidate country groups and their proposed roles. The final sampling frame depends on documented data availability.

The data inventory and its intended analytical uses are summarized in Table 2.

As summarized in Table 1, the listed countries are candidates for inclusion, not a confirmed empirical sample; this does not imply that each country has complete data on photovoltaic investments and financial losses. Country-level risk predictions can cover a broad range, while project-level economic loss predictions should be limited to a subsample of projects with reliable labels.

Let the set of all study countries be $\mathcal{C}$, the set of PV projects be $\mathcal{P}$, and the set of observation months be $\mathcal{T}$. This study constructs country-month data, country-relationship-month data, and project-month data, respectively, to form a multi-level dynamic risk analysis system.

2) Data Sources and Variable Definitions

Table 2 details the proposed data sources, variables, reporting frequencies, and modeling purposes. These publicly accessible databases and project disclosures span six broad categories: geopolitical risk, news text, national governance, project economic attributes, photovoltaic resources, and international energy markets [17]–[19], [22].

For D1–D3, this study focuses on using event and news data to construct dynamic geopolitical risk profiles and employs independently verified event records to generate predictive supervisory signals.

For D4–D5, the data primarily reflect a country's long-term institutional environment and macroeconomic characteristics.

For D6–D8, the analysis further maps country-level geopolitical risks to actual photovoltaic investment projects and constructs project costs, cash flows, and financing parameters.

D9 is used to analyze the potential economic linkages of shocks in the international energy market, while D10 is used to establish a real-world network of relationships among countries, investors, and projects.

Due to differences in temporal frequency and update mechanisms across various data sources, a unified monthly observation window is adopted for feature alignment; however, the actual publication dates of the original information are retained to prevent annual statistical data or subsequent project outcomes from being incorporated into the model prematurely.

B. Experimental Results

Figure 5 illustrates changes in new installed capacity and the energy technology mix of Africa's energy system for the 2015–2030 planning horizon under different political-risk constraints. Specifically, Figures 5(A)–(D) correspond to optimization scenarios with political risk levels of 29.1 (cost minimization), 20, 10, and 1, respectively. As shown in the figure, as the permissible level of political risk gradually decreases, the new installed capacity and technology mix of Africa's energy system undergo significant changes. The most prominent feature is the continuous expansion of solar photovoltaic (PV) installed capacity, while some wind and hydropower investments—which previously relied on cross-border supply—are gradually being replaced by local PV generation. Under the cost-minimization scenario, the system's

Table 1: Candidate African Countries and Their Roles in the Experimental Framework

Region	Candidate Countries	Main Research Variables	Experimental Role
North Africa	Egypt, Morocco, Algeria, Tunisia, Libya	Policy stability, energy trade, solar photovoltaic resources, international financing	Regional heterogeneity and policy risk
West Africa	Nigeria, Ghana, Senegal, Niger, Mali	Security incidents, financial risk, project financing, cross-border trade	High-risk event prediction
East Africa	Kenya, Ethiopia, Tanzania, Uganda, Rwanda	Cross-border infrastructure, inter-country linkages, project development	Dynamic risk transmission
Central Africa	Democratic Republic of the Congo, Cameroon, Chad	Political security, energy infrastructure, investment environment	Spatial risk heterogeneity
Southern Africa	South Africa, Namibia, Zambia, Mozambique	Photovoltaic development, financing structure, energy-system interconnections	Investment decision-making and case analysis

Table 2: Multisource Datasets for Geopolitical Risk Prediction and Photovoltaic Investment Optimization

Dataset	Data Source	Main Variables	Temporal Granularity	Experimental Use
D1: Political and Security Events	ACLED	Conflict, protests, violent events, event locations, event dates	Event-level / Daily	Risk-event labeling and validation
D2: Global News Events	GDELT 2.0	Event actors, countries, event codes, reporting time, news text	Event-level / Daily	LLM-based risk identification
D3: AI Geopolitical Risk Index	AI-GPR	Country risk, bilateral risk, threats, realized actions, oil-related risk	Monthly / Daily	External risk benchmark
D4: National Governance	World Bank WGI	Political stability, regulatory quality, government effectiveness, rule of law	Annual	Country-level structural features
D5: Macroeconomic and Financial Data	World Bank WDI, IMF	Exchange rates, inflation, GDP, interest rates, debt indicators	Annual / Quarterly / Monthly	Exogenous economic features
D6: Photovoltaic Projects	World Bank PPI, disclosures from developers and financing institutions	Project country, investment amount, installed capacity, financing entities, project status	Project-level	Project risk prediction
D7: Solar Energy Resources	Global Solar Atlas	GHI, DNI, PVOUT, geographic location	Spatial grid / Long-term average	Technical and economic parameters for photovoltaic development
D8: Cost of Capital	IEA Cost of Capital Observatory and project financing disclosures	WACC, financing conditions, risk premium	Annual / Project-level	Investment returns and financing costs
D9: Energy Market	EIA, public energy statistics, and relevant market databases	WTI crude oil price, energy price fluctuations	Monthly	Control variables for energy shocks
D10: Cross-Border Linkages	Project announcements, trade statistics, electricity transactions, and financing disclosures	Cross-country investment, equipment supply, electricity flows, and financing relationships	Annual / Project-level	Dynamic heterogeneous graph construction

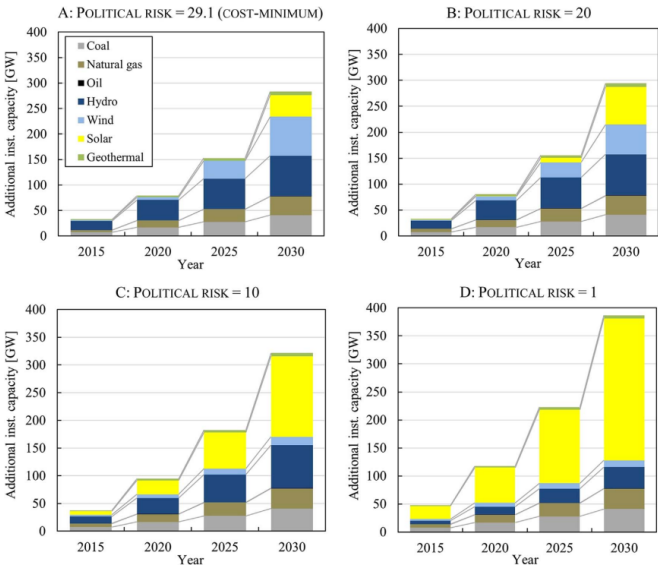


Figure 5: Comparison of additional installed generation capacity and photovoltaic investment allocation in Africa under different political-risk constraints. (A) Cost-minimization scenario with political risk of 29.1; (B) political risk of 20; (C) political risk of 10; and (D) political risk of 1. Different colors represent additional installed capacity from coal, natural gas, oil, hydropower, wind, solar, and geothermal energy

new installed capacity in 2030 is 283.2 GW, with energy investment primarily composed of hydropower, wind power, and fossil fuels, while the share of PV is relatively low; when the political risk constraint is tightened to 10, the new installed

capacity increases to 321.5 GW, and the share of PV in the new capacity rises significantly; when political risk is further reduced to 1, new installed capacity in 2030 approaches 390 GW, with solar PV becoming the primary component of new installations. This shift indicates that political risk constraints can significantly influence the technological choices and spatial allocation of energy investments; as risks associated with cross-border energy dependence are more strictly controlled, the optimization model tends to increase investment in domestic solar PV to reduce reliance on politically unstable countries and cross-border transmission networks. At the same time, since the capacity factor of solar PV is typically lower than that of some of the energy technologies it replaces, meeting the same electricity demand may require higher installed capacity and entail additional system investment costs.

To illustrate how conventional and AI-derived indices characterize geopolitical shocks, Figure 6 compares the temporal evolution patterns of AI-GPR [23] and the traditional geopolitical risk index, GPR AER, before and after six major geopolitical events related to Africa, including the 1956 Suez Crisis, the 1994 Rwandan Genocide, the 2011 Libyan Civil War, the 2020 Tigray War in Ethiopia, the 2023 armed conflict in Sudan, and the 2023 coup in Niger. As shown in the figure, both risk indices generally exhibited relatively stable fluctuations prior to major events, but both demonstrated sudden spikes of varying degrees around the time of the events, followed by a gradual decline, reflecting the non-stationary, time-concentrated, and persistent characteristics of geopolitical shocks. Specifically, in the scenarios corresponding to the Suez Canal crisis, the Rwandan genocide, and the Tigray War in Ethiopia, the peak value of GPR AER following the

events was higher than that of AI-GPR, and it exhibited more pronounced short-term fluctuations during certain phases; In the scenario corresponding to the 2023 armed conflict in Sudan, the AI-GPR reached a higher peak and maintained relatively high risk levels afterward, demonstrating a more sustained risk response; whereas in the Niger coup scenario, the GPR AER exhibited a more pronounced short-term peak. These differences suggest that the two risk measurement methods may exhibit distinct characteristics with respect to event semantic understanding, sensitivity to news coverage, characterization of risk persistence, and filtering of anomalous fluctuations. However, based solely on differences in the peaks of the risk index curves, it is not yet possible to determine which method possesses higher risk identification accuracy or earlier early-warning capabilities.

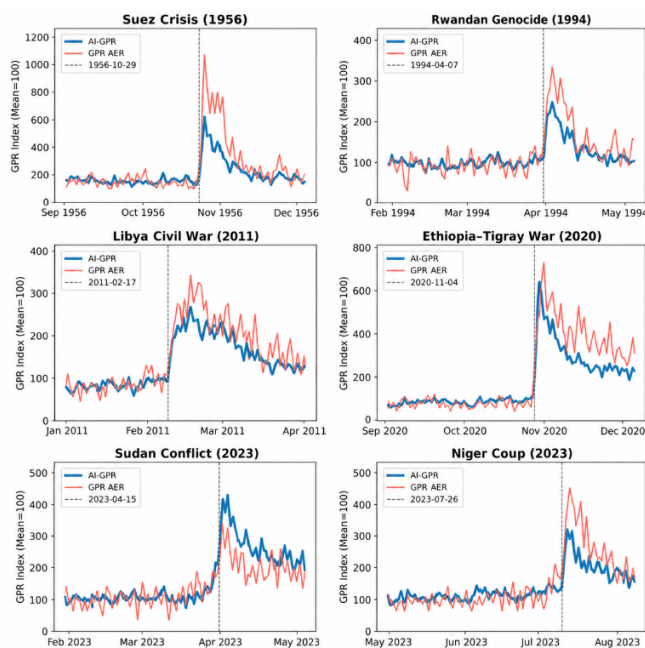


Figure 6: Illustrative comparison of dynamic responses of the AI-GPR and conventional GPR AER indices around major geopolitical events involving African countries

Figure 7 illustrates the trends in cross-border electricity exports by 2030 for five major African electricity-exporting countries—the Democratic Republic of the Congo (DRC), Somalia, Ethiopia, Sudan, and Libya—under different political-risk constraints, revealing the potential impact of geopolitical risk tolerance levels on regional energy trade patterns and the allocation of renewable energy investments. The horizontal axis of the figure represents the maximum level of avoidable political risk permitted by the system, while the vertical axis represents each country's annual electricity export volume in 2030 (TWh). As shown in the figure, as the level of political risk tolerance gradually increases, the scale of cross-border electricity exports across these countries exhibits distinct non-linear growth and differentiated threshold responses. Among them, the Democratic Republic of the Congo shows the most

significant change: when the risk constraint threshold rises from approximately 4 to 13, its electricity export volume rapidly increases to about 120 TWh and remains largely stable thereafter, indicating that a cost-minimization-oriented energy system relies heavily on the country's abundant hydropower resources. In contrast, Ethiopia can maintain a certain scale of electricity exports even at lower risk tolerance levels; its export volume reaches 58 TWh when the risk threshold is approximately 20, demonstrating relatively strong adaptability to cross-border power supply; Sudan and Libya reached export levels of approximately 43 TWh and 24 TWh, respectively, when the risk threshold was raised to about 18 and 15, while Somalia's electricity exports were more sensitive to political risk constraints, showing significant growth only after the risk threshold exceeded approximately 26 and ultimately reaching about 64 TWh. These results indicate a significant trade-off between the economic efficiency of cross-border electricity trade and geopolitical risks: easing political risk constraints can expand the scale of electricity exports for countries with resource advantages, but may simultaneously increase the regional energy system's dependence on countries with higher political risks; conversely, tightening risk constraints would prompt the energy system to reduce certain high-risk cross-border electricity transactions and supplement electricity supply by increasing the proportion of investment in local renewable energy sources, such as solar photovoltaics.

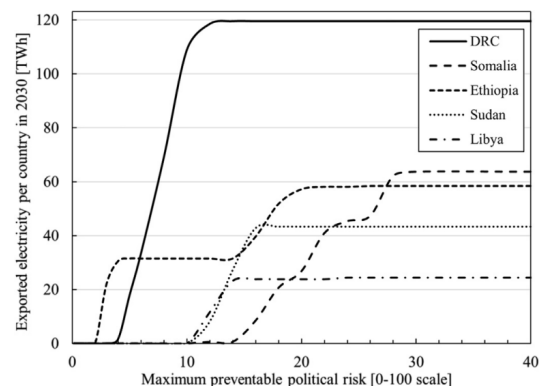


Figure 7: Cross-border electricity export volumes of major african electricity exporters in 2030 under different political-risk constraints

Figure 8 illustrates the long-term temporal evolution of the Geopolitical Risk Acts (GPR Acts) and Geopolitical Risk Threats (GPR Threats) indices from 1960 to 2025. Both indices were smoothed using a 30-day moving average and normalized to 100 based on the average levels from 1985 to 2019. As can be seen from the figure, geopolitical risk exhibits significant non-stationarity, phased fluctuations, and sudden shocks. There is a dynamic correlation between actual risk behavior and potential risk threats, yet this relationship also displays marked asymmetry. In the early 1960s, the threat index reached short-term peaks exceeding 300, while fluctuations in the behavior index were relatively limited, reflecting that geopolitical tensions may rise significantly be-

fore actual conflict behavior occurs; around 1990 and during the period from 2001 to 2003, the behavior index reached distinct peaks exceeding 300, accompanied by an increase in the threat index, illustrating the concentrated impact of major geopolitical events on risk levels; Particularly since 2022, the behavioral index has reached localized peaks exceeding 400, and from 2024 to 2025, both indices have shown a relatively pronounced upward trend, indicating that the international geopolitical environment has continued to be characterized by high uncertainty in recent years. Furthermore, the timing of the peaks, the magnitude of changes, and the duration of these trends for the two indices are not entirely consistent, suggesting that geopolitical risks exhibit two distinct dynamic manifestations: the accumulation of potential threats and the occurrence of actual risk events. A single, comprehensive risk index may struggle to fully capture this distinction.

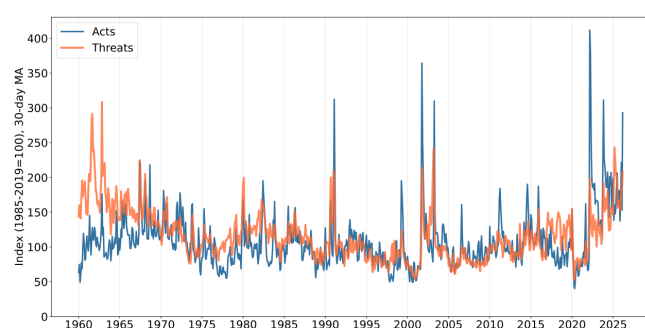


Figure 8: Long-Term Dynamics of Geopolitical Risk Acts and Threats and Their Implications for Modeling

For the proposed EG-GeoInvest framework, these patterns provide an important basis for constructing a multidimensional, event-driven mechanism for identifying and predicting geopolitical risks. Specifically, this study utilizes evidence-constrained generative artificial intelligence to extract semantic features of geopolitical risk threats and actual risk behaviors from multilingual political news, policy announcements, and texts related to cross-border investment, respectively, using the temporal convolutional network (TCN) within the ST-GREM module to capture the accumulation process, impact persistence, and attenuation patterns of risk threats, and combining this with a relationship-aware graph convolutional network (GCN) to model the potential interrelated impacts of risk behaviors across transnational energy trade, international financing, and photovoltaic equipment supply networks. Building on this, national-level dynamic risk information is mapped to transnational photovoltaic projects in Africa to further predict the potential impacts of political conflicts, policy changes, and cross-border supply chain disruptions on project construction progress, financing costs, and expected cash flows. The predicted risk distributions are then incorporated into Conditional Value-at-Risk (CVaR) and distribution-robust investment optimization models, thereby bridging the gap between dynamic geopolitical risk identification and risk-aware investment decision-making.

Figure 9 illustrates the long-term dynamic evolution of the Global Petroleum-Related Geopolitical Risk Index (GPR-Oil Index) and West Texas Intermediate (WTI) crude oil prices from 1960 through the observation date in 2026. The blue curve represents the 30-day moving average of the GPR-Oil Index, plotted on the left logarithmic axis; the red curve represents the WTI crude oil price denominated in constant 2026 June U.S. dollars, plotted on the right-hand linear axis. As shown in the figure, the global energy market exhibits significant geopolitical risk shocks, energy price volatility, and periodic nonlinear correlations. From the late 1970s to the early 1980s, both the oil geopolitical risk index and WTI prices rose markedly, reflecting a potentially strong correlation between international political tensions and changes in energy market prices; around 1990, the risk index reached a significant short-term peak, while the magnitude and duration of the crude oil price response were relatively limited, indicating marked heterogeneity in the market impacts of different geopolitical shocks; Around 2008, WTI prices briefly approached \$200 per barrel, while the risk index did not maintain a proportional increase over the same period, indicating that changes in energy prices are closely related not only to geopolitical events but also to global energy supply and demand, economic cycles, and financial market conditions.

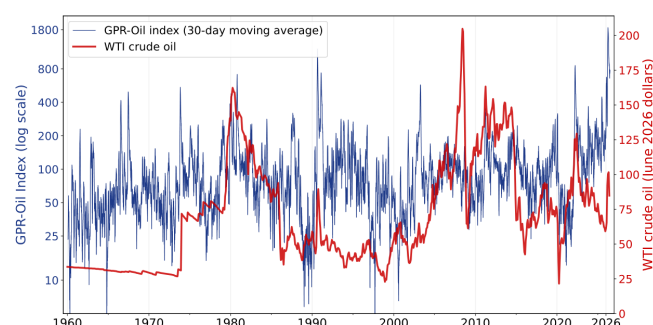


Figure 9: Long-Term Evolution of Global Oil-Related Geopolitical Risk and International Crude Oil Prices

Around 2020, crude oil prices fell significantly, while the risk index continued to exhibit some volatility, further illustrating that there is no stable, synchronous relationship between the two types of indicators. Specifically, during the period from 2022 to 2026, the oil geopolitical risk index experienced multiple episodes of sharp volatility, approaching 1,800 at certain points, while WTI prices did not consistently exhibit corresponding increases. This suggests that there may be nonlinear, time-lagged, and asymmetric response mechanisms between geopolitical risks and energy market prices. For the EG-GeoInvest framework proposed in this study, the aforementioned dynamic characteristics provide an important basis for constructing a multimodal risk prediction model that integrates geopolitical events, energy market prices, and cross-border investment relationships. Specifically, this study uses evidence-constrained generative AI to extract semantic features of risk events such as international energy policies,

political conflicts, energy supply disruptions, and cross-border trade restrictions; employs the Time Convolutional Network (TCN) within the ST-GREM module to capture multiscale dynamic changes in geopolitical risks and energy prices; and utilizes a relationship-aware Graph Convolutional Network (GCN) to characterize the potential interlinked impacts of relevant shocks across networks of inter-country energy trade, equipment supply, international financing, and photovoltaic investment. During the project economic risk modeling phase, changes in international crude oil prices can serve as exogenous variables influencing transportation costs, construction expenses, macroeconomic inflation, and the competitive environment for alternative energy sources. These variables, along with characteristics of the PV project site—such as solar resources, capital costs, and energy policies—are jointly fed into the project-level risk prediction module to analyze changes in project delay probabilities, cash flow losses, and risk-adjusted net present value under different geopolitical scenarios.

Figure 10 illustrates the long-term trends in geopolitical risk correlation indices among nine pairs of African countries, including Egypt–Libya, Ethiopia–Eritrea, Nigeria–Niger, Sudan–South Sudan, Egypt–Ethiopia, Morocco–Algeria, Kenya–Somalia, Rwanda–Democratic Republic of the Congo, and Algeria–Mali. The aim is to reveal the temporal heterogeneity, sudden shocks, and cross-border interdependence characteristics of geopolitical risks under different bilateral relationships.

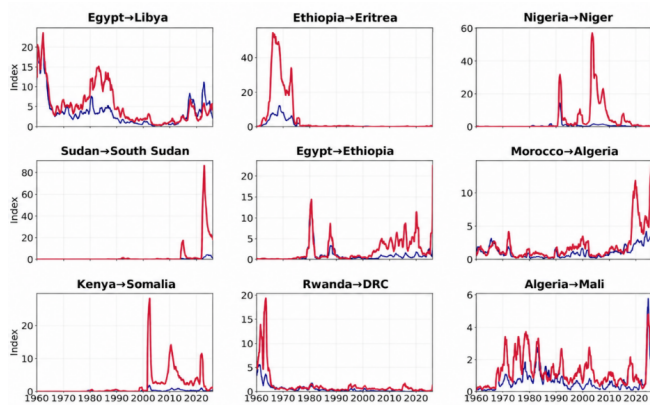


Figure 10: Long-Term Evolution of Geopolitical Risk Associations among African Countries and Their Implications for Cross-Border Photovoltaic Investment

As shown in the figure, the risk evolution patterns vary significantly across different country pairs. For some country pairs, the relationship alternates between short-term sharp fluctuations and long-term low-risk periods, while for others, the relationship exhibits a sustained accumulation of risk and multiple localized peaks. Specifically, the Egypt–Libya and Ethiopia–Eritrea pairs exhibited high risk volatility in the early stages of the time series shown in the figure, followed by a gradual decline; the Nigeria–Niger and Kenya–Somalia pairs

exhibited strong characteristics of sudden peaks, indicating that risk correlations may undergo distinct phased changes; the Sudan–South Sudan pair exhibited a significant peak in the latter part of the sequence, while the Egypt–Ethiopia and Morocco–Algeria pairs displayed risk fluctuations across multiple phases and an upward trend in the later stages; in contrast, the Rwanda–Democratic Republic of the Congo and Algeria–Mali pairs exhibited varying degrees of low-frequency fluctuations and localized risk clustering. The differences in risk peaks, duration, and fluctuation amplitude between the red and blue curves in the figure suggest that different risk characterizations may capture information on inter-state correlations of varying intensity and temporal scales; however, until the specific definitions of the indicators for both curves are clarified, they cannot be directly interpreted as actual conflict intensity or model prediction accuracy. For the EG-GeoInvest framework proposed in this study, such inter-state risk time series can provide an important analytical perspective for modeling the transnational propagation of geopolitical risks. By using evidence-constrained generative AI to extract semantic features of inter-state political conflicts, changes in diplomatic relations, energy policies, and cross-border economic events, and by utilizing the temporal convolutional network (TCN) in the ST-GREM module to capture the persistence, abrupt changes, and multiscale temporal dependencies of risk correlations, while simultaneously combining a relationship-aware graph convolutional network (GCN) to construct a dynamic, directed, and heterogeneous network of —investor—PV project, further characterizing the potential interrelated impacts of geopolitical risks arising from international investment, energy trade, equipment supply, and financing relationships.

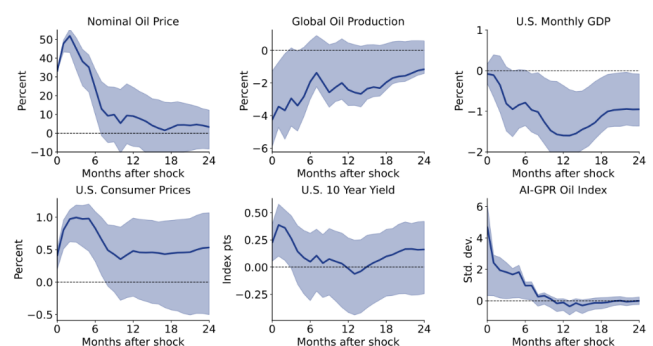


Figure 11: Dynamic Responses of Energy Markets and Macroeconomic Variables to Geopolitical Energy-Risk Shocks

Figure 11 illustrates the dynamic impulse response characteristics of international crude oil prices, global oil production, U.S. monthly GDP, consumer prices, 10-year Treasury yields, and the AI-GPR oil risk index within 24 months following an oil-related geopolitical risk shock. The blue solid lines represent the estimated response paths for each variable, the light blue shading indicates the uncertainty intervals of the

estimates, and the horizontal axis represents the months following the shock. As shown in the figure, geopolitical energy risk shocks exert significant nonlinear, heterogeneous, and persistent effects on international energy markets and macroeconomic variables. First, nominal crude oil prices rise rapidly in the initial phase following the shock, peaking at nearly 50%, before gradually declining and falling below 10% approximately 12 months later. This indicates that energy prices exhibit strong short-term sensitivity to geopolitical events, but the impact of the shock gradually weakens over time.

At the same time, global oil production exhibited a negative response of approximately 4% in the early stages of the shock. Although it gradually recovered thereafter, it remained at negative levels for 24 months, reflecting that geopolitical tensions may create persistent supply constraints through energy supply disruptions and production adjustments. From a macroeconomic perspective, U.S. monthly GDP showed a negative response following the shock, reaching a low of approximately -1.5% around the 12-month mark before gradually recovering; consumer prices rose by about 1% initially and subsequently maintained a relatively moderate positive response, suggesting that the geopolitical risk shock to energy may simultaneously exert pressure on economic growth and trigger cost-push inflation. The yield on 10-year U.S. Treasury bonds rose briefly at the onset of the shock and subsequently fluctuated around the zero response level, indicating a high degree of uncertainty regarding interest rate adjustments.

By contrast, the AI-GPR oil-risk index rises rapidly to approximately 5 standard deviations upon the occurrence of a shock, then declines steadily, approaching the baseline level after about 9–12 months. This suggests that the index response to the risk event itself may subside relatively quickly, while the impacts on energy supply and the macroeconomy persist for a longer duration. This dynamic disparity between risk signals and economic consequences provides an important basis for modeling risk transmission within the EG-GeoInvest framework proposed in this study. Specifically, this study uses evidence-constrained generative AI to identify risk events such as international energy supply disruptions, political conflicts, energy trade restrictions, and related policy changes. It employs a temporal convolutional network (TCN) within the ST-GREM module to extract the short-term response, time lags, and long-term decay characteristics of risk shocks, and combines this with a relationship-aware graph convolutional network (GCN) to characterize the potential interconnected impacts of external energy shocks across networks of cross-border trade, equipment supply, international financing, and photovoltaic project investment. Building on this, international oil prices, macroeconomic inflation, financing conditions, and country-level geopolitical risks are treated as exogenous information for project risk forecasting. The study analyzes the impact of energy cost fluctuations on PV project construction costs, equipment transportation expenses, capital costs, and expected cash flows, and uses generative large language models and a multi-task risk forecasting module to estimate the probability of project delays and the distribution

of potential economic losses.

VII. Conclusion

Addressing issues such as the complex and dynamically evolving geopolitical risks associated with transnational photovoltaic projects in Africa, the difficulty in characterizing cross-border risk interdependencies, and the lack of risk awareness in traditional investment decision-making, this study proposes a framework for geopolitical risk prediction and robust investment decision-making (EG-GeoInvest) that integrates generative artificial intelligence with spatiotemporal graph neural networks. By integrating geopolitical events, multilingual news, national governance indicators, and PV investment data, this framework establishes an evidence-constrained, multisource, heterogeneous risk characterization mechanism to enable the structured extraction of dynamic risk information. Building on this, the ST-GREM module—which fuses temporal convolution with relationship-aware graph convolution—is designed to jointly model the temporal dependence, cross-national correlations, and project heterogeneity of geopolitical risks. Through cross-modal semantic projection and LoRA fine-tuning, the framework enables collaborative learning between graph-structured features and generative language models, establishing a probabilistic prediction mechanism for risk events, project delays, and economic losses. Furthermore, the predicted risk distribution is incorporated into a conditional value-at-risk and distribution-robust optimization model, resulting in a project allocation method that balances investment returns with the control of extreme losses.

Author Contributions

All authors contributed equally to this work.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding Information

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