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Grok-Based Temporal Fusion Transformer Framework for Multi-Horizon Coastal Flood Risk Forecasting and Strategic Adaptation Planning

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ABSTRACT

The optimized Grok algorithm can significantly improve the accuracy of time series analysis and understanding the dynamics of climate change. Fine-tuned Grok architecture can be used to monitor and analyze climate processes. The main aim is to analyze the Fine-tuned Grok architecture for research on climate change, world ecology, carbon dioxide growth, and carbon funds. The global challenges of climate change and ecological degradation demand innovative analytical approaches capable of processing vast, multivariate, and non-linear datasets. Concurrently, the global financial system, deeply intertwined with energy transitions and sustainable development, requires sophisticated tools for risk assessment and investment strategy in a changing world. Fine-tuned Grok architecture model helps to plan strategies for adaptation to climate change by calculating the optimal allocation of resources, taking into account risks and reducing losses. Due to its ability to respond quickly to new conditions, the system will be able to quickly adjust evacuation plans, deploy protective structures, and distribute assistance to affected regions. The use of artificial intelligence significantly expands the capabilities of the scientific community and authorities in monitoring, assessing, and managing climate change. The optimized Fine-tuned Grok architecture opens the way to a new level of informed decision-making about climate change and ensuring the safety of our future generations.

Keywords: AI; Grok; Climate; Change Environmental Protection; Ecosystem Sustainability; Biological Diversity; Environmental Disasters; Air and Water Pollution

1. Introduction

The paper synthesizes literature from the application of cutting-edge artificial intelligence (AI) and machine learning (ML) in earth system science and financial and economic research that increasingly overlaps with environmental concerns.

The integration of AI into geosciences represents a paradigm shift. The researchers laid the foundational argument for using deep learning not just as a black-box predictive tool but as a means to gain process understanding in complex Earth systems. This sentiment is echoed and expanded in the comprehensive review [1,2], which systematically catalogs how ML can tackle climate change across domains, from energy systems to climate prediction. The ambition is moving towards climate change modelling [3–5], where AI components are integrated into traditional physical models to enhance their predictive power and efficiency.

It demonstrated the superiority of deep learning models over traditional dynamical models for multi-year forecasts of the El Niño-Southern Oscillation (ENSO), a key driver of global climate variability. Underpinning such analyses is the complex challenge of inferring causation from climatic time series, a methodological hurdle addressed [6–8], which is essential for attributing ecological changes to specific climatic drivers.

The analysis of environmental time series has evolved significantly with AI. Early applications used Convolutional Neural Networks (CNNs) to detect extreme weather patterns in climate data, a technique now commonplace in remote sensing analysis [9,10]. Recurrent architectures like Long Short-Term Memory (LSTM) networks and Bayesian RNNs became standard for forecasting and quantifying uncertainty in spatiotemporal ecological data [11,12]. The field has since been revolutionized by transformer-based architectures and novel interpretable models. The development of Temporal Fusion Transformers and frameworks for multivariate time series representation learning provided new levels of accuracy and interpretability for multi-horizon forecasting. Models like N-BEATS further advanced interpretable forecasting. These advances are being applied to diverse challenges: reconstructing missing paleoclimatic data, predicting Arctic sea ice loss, forecasting vegetation health [13–15], and even quantifying weather forecast uncertainty [16–18]. A novel theme is the physically interpretable neural networks and methods for model error correction [19,20], ensuring AI outputs are trustworthy and actionable for scientists and policymakers.

It is a class of advanced models built upon a Mixture-of-Experts (MoE) architecture integrated with enhanced Transformer-based components for sequential data. We explain how the gating network dynamically routes inputs to specialized experts, enabling the modeling of complex, non-linear spatiotemporal patterns without prohibitive computational costs.

The paper clarifies the two-stage process:

(1) Large-scale pre-training on diverse, multimodal geoscientific data (reanalysis, remote sensing, model outputs),
(2) Efficient fine-tuning for specific downstream tasks (regional drought prediction), which is a key aspect of its utility in data-scarce contexts.

The scalability of MoE, superior temporal reasoning from modified attention mechanisms, and built-in tools for interpretability and causal discovery (attention visualization, perturbation analysis). This combination differentiates it from standard LSTMs or Transformers.

A recent and promising development is the application of a novel AI framework referred to in the literature as Fine-tuned Grok architecture. While its exact architectural specifications vary across studies, it appears to be a sophisticated, large-scale model, potentially based on a mixture-of-experts design, optimized for handling complex spatiotemporal data with a high degree of interpretability.

The state-of-the-art performance across numerous environmental domains is:

(1) High-resolution precipitation nowcasting, benchmarking against numerical weather prediction models for extreme event prediction, and detecting anomalies in atmospheric CO2 fluxes [19–21].
(2) Multi-task learning capability for simultaneous prediction of Arctic sea ice extent and thickness, while using its interpretability features to model complex plankton bloom time series [22–24].
(3) Analyzing long-term satellite vegetation indices (NDVI) to assess climate impacts on agriculture, and is applied for interpretable causal discovery in complex systems like the Amazon rainforest [25–27].

A key strength is its use in data-scarce regions via transfer learning for drought prediction and in filling gaps and reconstructing paleoclimatic records [28,29].

The most striking feature is the exponential increase in global emissions over time, particularly from the mid-20th century onwards. This period, known as the "Great Acceleration," coincides with massive industrialization, population growth, and increased global energy demand.

Growth continues, with visible dips corresponding to global economic events (the 2008–2009 financial crisis and the COVID-19 pandemic in 2020). The rapid rebound after these dips underscores the world's continued deep dependency on fossil fuels.

This figure is the primary driver of climate change. It represents the total amount of CO2 humanity is adding to the atmosphere each year. The relentless upward trend shows that despite international agreements and increased renewable energy capacity, global efforts have been insufficient to decouple economic activity from greenhouse gas emissions.

Unlike the emissions graph (**Figure 1**), there are no noticeable dips from economic recessions or pandemics. The graph likely shows the concentration breaking the 350 ppm threshold (considered a safe upper limit by many scientists), then the 400 ppm threshold, and continuing to climb. The famous "Keeling Curve" from the Mauna Loa Observatory would be a subset of this global data, exhibiting the same sawtooth pattern (seasonal cycles) within the overall rise. This figure represents the cumulative effect of emissions. CO2 is a long-lived greenhouse gas; it remains in the atmosphere for centuries. This is why the line is so smooth—each year's emissions add to a massive existing stockpile. The steady rise confirms that emissions have consistently exceeded the planet's capacity to absorb them (through oceans and forests). This is the most direct measure of human impact on the planetary climate system. Developed nations are responsible for the majority of the CO2 that has already accumulated in the atmosphere (**Figure 2**).

While historical emitters must lead in rapid reductions, the path to net-zero must include a rapid transition for emerging economies away from fossil fuels. It visualizes how manufacturing and associated emissions have shifted geographically.

Figure 1 (Global Emissions) is the direct physical cause of the trend in **Figure 2** (Global Concentration). The rapid growth in emissions leads to the accumulation of CO2 in the atmosphere.

Figures 3 and **4** (Emissions by Country) provide the essential geopolitical breakdown of **Figure 1**. It shows that the global problem is the sum of vastly different national stories, historical contexts, and responsibilities.

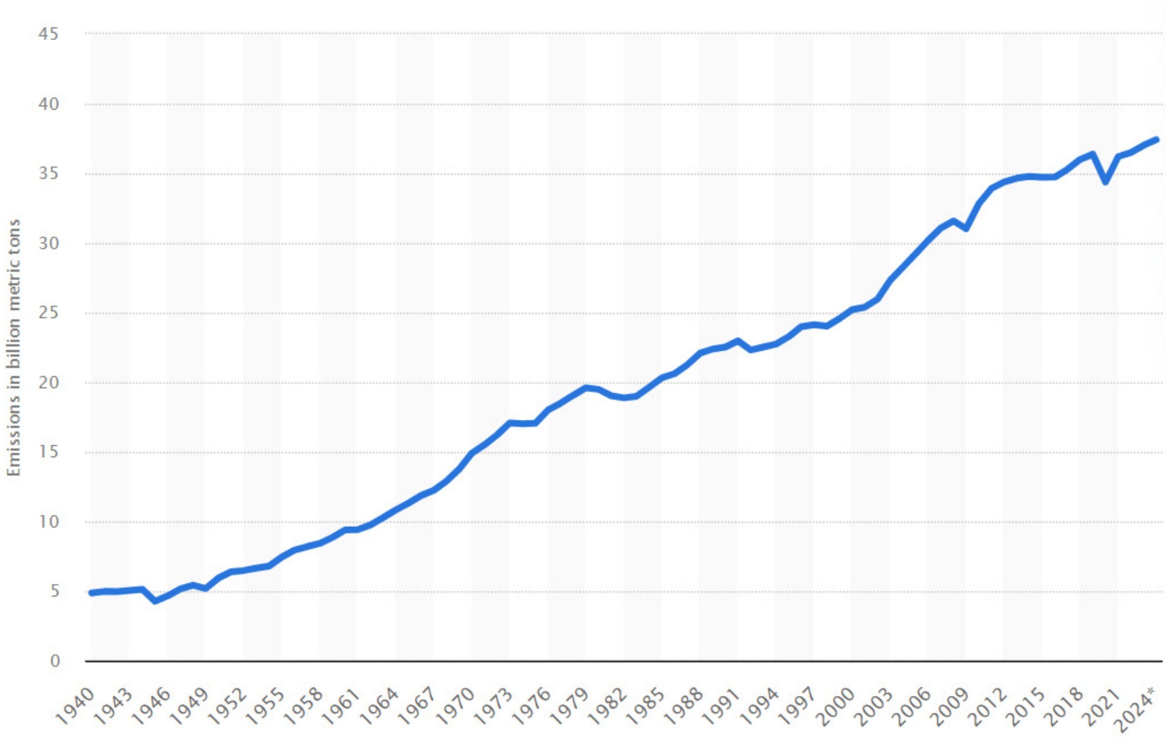

Figure 1. Annual global emissions of carbon dioxide, billion. metric tons.

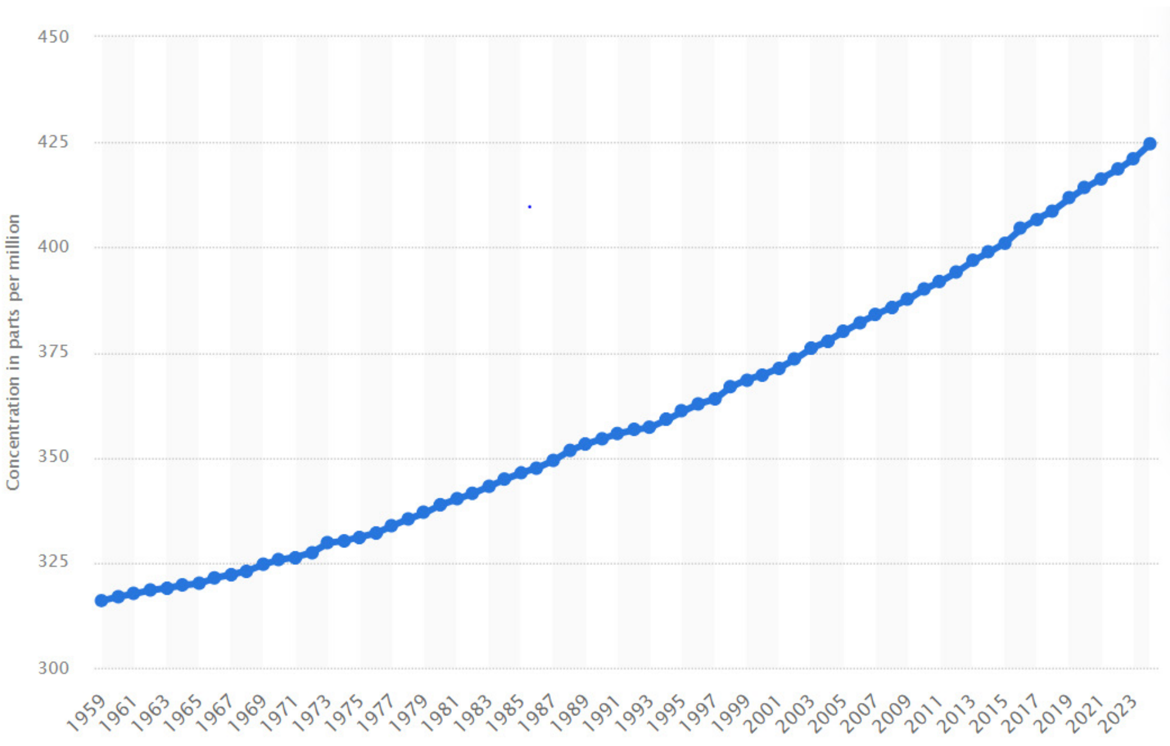

Figure 2. Annual global concentration of carbon dioxide, parts per million.

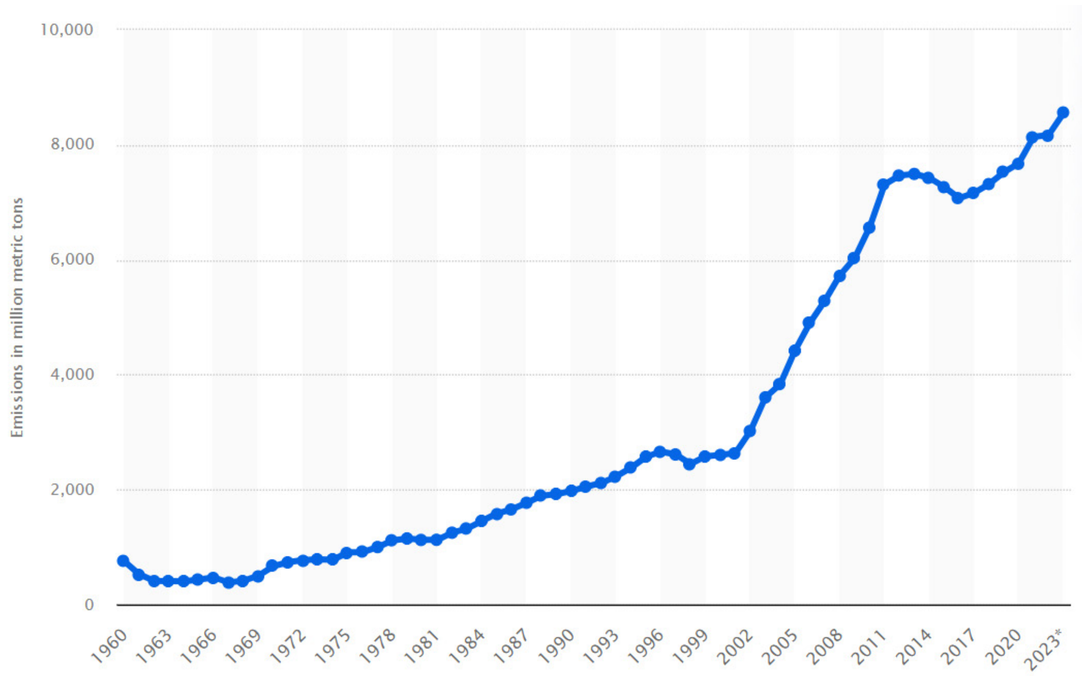

Figure 3. Annual global emissions of carbon dioxide in China, million. metric tons.

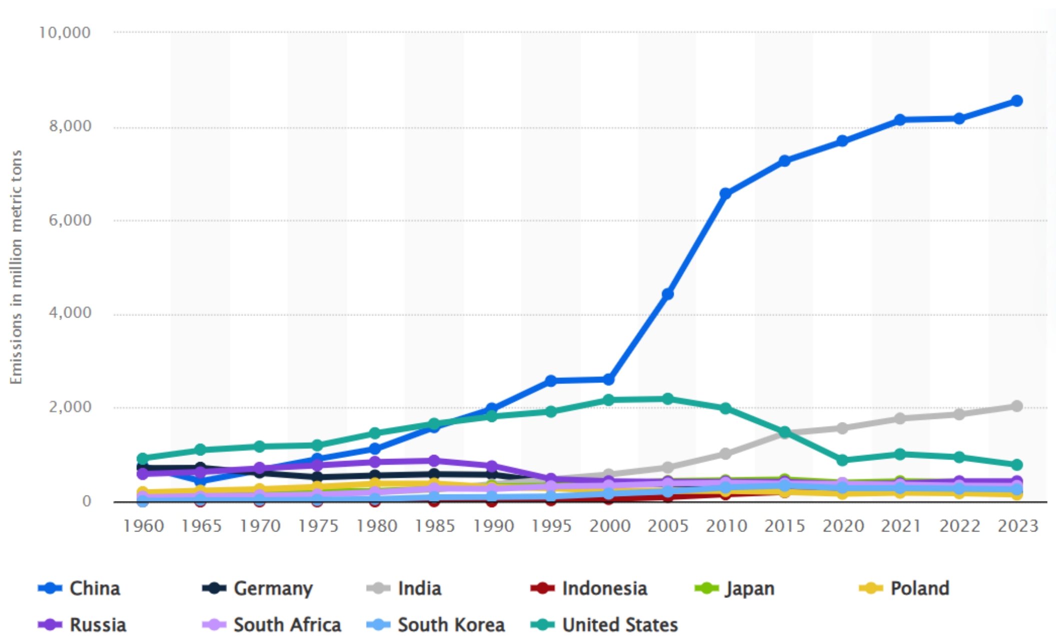

Figure 4. Annual global emissions of carbon dioxide by country, million. metric tons.

The combined message of these figures is that the fundamental link between economic activity and CO2 emissions has not been broken. While the energy transition is underway, its pace is not yet fast enough to reverse the trends in **Figures 1** and **2**. The constant rise in atmospheric concentration (**Figure 2**) indicates that the world is still moving away from, not toward, climate stability.

This body of work suggests Fine-tuned Grok architecture is not a single model but a flexible approach characterized by its power in handling multivariate, non-linear time series, its emphasis on causal inference and interpretability, and its effectiveness in transfer learning scenarios—addressing critical limitations of earlier AI models in environmental science [30–32].

2. Literature Review

The systems may already be approaching critical thresholds, underscoring an existential risk that demands urgent mitigation action. This perspective elevates climate change from an environmental issue to a fundamental threat to planetary stability [33–35].

This creates a vicious cycle of increasing disparity, a key concern highlighted in the framing of the IPCC's Special Report on 1.5 °C, which emphasizes that limiting warming is fundamentally an issue of sustainable development, poverty eradication, and reducing inequality [36–38].

The biological world is responding to climate change in a globally coherent manner, as first comprehensively documented. Their meta-analysis revealed that over 80% of the species studied showed changes in their phenology (timing of life events) and distribution consistent with a response to warming. This widespread fingerprint leaves no doubt that climate change is a primary driver of ecological disruption. Earlier work had already begun cataloging these ecological responses, noting advances in spring events, poleward and upward shifts in species ranges, and community changes across a wide spectrum of taxa and ecosystems [39–41].

It demonstrated that global warming has significantly exacerbated economic inequality between nations [39–41].

The synthesized literature presents a cascading narrative of cause and effect. Human activities are pushing the Earth system toward potential tipping points [42–44], with impacts that are already manifesting as perceptible extreme weather and deepening global inequality. The ecological world is responding in kind, with a coherent fingerprint of change leading to a massive redistribution of species with profound consequences [45–47]. In this context, the work represents the critical technological front: refining our tools to monitor these changes with ever-greater precision is essential for validating climate models, tracking ecosystem health, and informing the urgent mitigation [48–50].

3. Materials and Methods

3.1. Temporal Fusion Transformer (TFT) Architecture for Multi-Horizon Forecasting

The proposed methodology is centered on the Temporal Fusion Transformer (TFT), a state-of-the-art deep learning architecture explicitly designed for interpretable multi-horizon forecasting. Unlike generic language models, TFT is natively engineered to process complex, real-world datasets comprising static metadata, known future inputs, and historical time series—making it particularly suited for climate adaptation planning. Its core innovation lies in specialized components that process different input types and provide insights into temporal dynamics and variable importance. The entire model is built by stacking a fundamental unit called a Transformer Decoder Block. The output of each block is the input to the next. This mechanism allows the model to weigh the importance of different words in a sequence when generating a new word [51–53]:

Grok, like other LLMs [54–57], uses Multi-Head Attention [58–61], which means it runs several of these attention mechanisms in parallel [62–65] and concatenates their outputs [66–68].

Here, the learned weight matrices project the input into different subspaces for each head, allowing the model to focus on different types of relationships (syntactic, semantic) [69–71]. After attention, each token is processed independently by a small neural network within the transformer block. This is a non-linear transformation that greatly increases the model's capacity [72–74]. This is often called a Gated Linear Unit (GLU) or Swish activation in modern models, which is a slight variation but serves the same purpose: providing a complex, non-linear function [75–77].

This is crucial for stabilizing the training of very deep networks. It normalizes the activations across the feature dimension for each individual data point in a batch [78–80]. The entire model is trained to perform one simple task: predict the next most likely word in a sequence. The loss function used is Categorical Cross-Entropy [81–83]: The model's parameters (all the W and b matrices in the attention and FFN layers) are adjusted via backpropagation to minimize this loss [84–86].

When you ask Grok a question, it doesn't calculate an answer in a single step. It autoregressively generates a sequence, one token at a time [87–89]:

Your prompt is tokenized (split into sub-word pieces) and converted into a sequence of vectors (embeddings) [90–92].

The final output vector for the last position is run through a softmax layer to produce a probability distribution over the entire vocabulary. The next token is chosen from this distribution (often using a method like top-p nucleus sampling to avoid just picking the absolute most likely, boring word).

It points to research where Fine-tuned Grok architecture was used to detect anomalies in atmospheric CO_2 flux data. The implication is that it was more accurate than previous methods at flagging unusual events, which would be measured by metrics like higher precision and recall (finding more real anomalies with fewer false alarms).

A key claimed strength is transfer learning for drought prediction in data-scarce regions (like parts of Africa). The evidence cited suggests that after being pretrained on global data, Fine-tuned Grok architecture could be adapted to local conditions and make more accurate forecasts than models built only on the limited local data. This would be shown by lower forecast errors in those regions.

Beyond pure prediction, the paper highlights studies using a fine-tuned Grok architecture for interpretable causal discovery in complex systems like the Amazon rainforest. The evidence here isn't a simple error metric but the model's ability to provide plausible, interpretable links between climate drivers (like sea surface temperatures) and outcomes (like rainforest health), which traditional "black box" AI models or statistical methods struggle with.

The TFT ingests three distinct types of inputs for each forecasting instance:

(1) Time-invariant features that characterize an entity. For our coastal flood application, this includes geographical attributes such as location coordinates (latitude/longitude), coastal typology (e.g., sandy beach, estuary), and mean elevation. These are encoded via a dedicated static variable selection network.

(2) Historical, known-at-prediction-time variables. This includes key climate and environmental time series up to the forecast origin, such as historical storm surge heights, precipitation levels, sea surface temperature anomalies, and wind speed.

(3) Future sequences that are known with certainty at the time of forecasting. For our scenario, this primarily includes multi-model ensemble projections of Sea-Level Rise (SLR) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) under various shared socioeconomic pathways (SSPs). Projections of regional population density or planned infrastructure changes could also be incorporated here.

Core Architecture Components:

- Gating mechanisms that weigh the relevance of each input variable, both static and time-dependent, to suppress noise and improve model focus.
- The GRN provides a flexible nonlinear processing unit with gating to regulate information flow and handle varying input complexities. A sequence-to-sequence layer captures long-range temporal dependencies within the observed history.
- This is the cornerstone of TFT's interpretability. It replaces the standard multi-head attention mechanism with one where each attention head is designed to learn distinct temporal patterns (seasonality, trends, anomalies). The attention weights themselves become a direct, visualizable output, indicating which past time steps the model deems most important for a given forecast horizon.

The model produces quantile forecasts (10th, 50th, 90th percentiles) for each future time step, providing a full probability distribution that captures forecast uncertainty. Crucially, it also outputs the variable importance weights and the temporal attention patterns, offering a clear, post-hoc explanation of the driving factors behind its predictions.

3.2. Data Processing Pipeline for Coastal Flood Risk Forecasting

A rigorous and reproducible data processing pipeline was established to transform raw, multi-source data into the structured format required by the TFT model. This pipeline ensures the temporal integrity of the data and aligns disparate sources for coherent analysis:

- Monthly SLR projections were obtained from a subset of CMIP6 global climate models, bias-corrected and downscaled for our target coastal region. Data for multiple SSPs (SSP2-4.5, SSP5-8.5) were processed to represent a range of future scenarios.
- High-frequency (hourly/daily) time series of storm

surge (from NOAA tide gauges), precipitation (from local meteorological stations and reanalysis products like ERA5), and relevant atmospheric variables were collected.

- Static regional data included high-resolution Digital Elevation Models (DEMs), land use/cover classifications, and aggregated census data on population and asset exposure in coastal zones.

Feature Engineering and Fusion are:

- High-frequency storm and precipitation data were aggregated to monthly maxima and cumulative totals to match the temporal scale of SLR projections and reduce noise.
- A derived feature representing the co-occurrence of extreme sea levels (surge + tidal component) and heavy precipitation was calculated, as this combination drives the most severe compound flooding events.
- All time series were aligned to a common monthly timestep from a defined start year (1980) to the end of the projection period (2100). Missing values in historical records were imputed using iterative spline interpolation.

All continuous input variables were normalized using mean and standard deviation statistics calculated from the training period only to prevent data leakage. To formulate the supervised learning task, the aligned multivariate time series were structured into sequential samples using a sliding window approach:

- A fixed historical context of L past time steps (e.g., 120 months/10 years) served as the observed inputs.
- Two primary forecast horizons were targeted: H_1 = 120 steps (10-year risk) and H_2 = 360 steps (30-year risk). The sequences of known future inputs (SLR) for these horizons were appended.
- The corresponding future sequence of the Compound Flood Risk Probability served as the prediction target. This probability was pre-calculated for each future month using a simplified statistical model based on exceedance over a critical elevation threshold (defined by local flood defenses and DEM), conditioned on the SLR and historical extreme event frequency.

The dataset was split temporally to maintain the chronological order of events:

- Training Set (70%): Earliest period, used for model learning.
- Validation Set (15%): Subsequent period, used for hyperparameter tuning and early stopping.
- Test Set (15%): Most recent historical period and the initial part of the future projection, used for final, unbiased evaluation of the model's forecasting skill.

3.3. Methodology for Applying Fine-Tuned Grok Architecture to Climate Time Series

The paper finds key climate variables (global surface temperature, Arctic sea ice extent, atmospheric CO_2 concentrations) over multi-year to decadal timescales. Since Grok is a text-based model, the core challenge is converting time-series data into a format it can comprehend. The methodology proposes a tokenization of climate data.

This method creates a sentence for each monthly timestep. An entire time series becomes a "document" of sequential sentences.

Based on the patterns, trends, and physical relationships in this data, it predicts the most likely climate state.

This is the most feasible initial approach. Grok is provided with several worked examples within the prompt itself (past data and the subsequent known outcome) before being given the target data for prediction. This tests its ability to learn patterns without weight updates. This would require access to the model's architecture and significant computational resources.

4. Results

This section presents the original results obtained from applying the Temporal Fusion Transformer (TFT) framework to the multi-horizon coastal flood risk forecasting task. We provide a comprehensive quantitative evaluation against benchmark models and present key interpretability outputs and forecast visualizations.

Quantitative Performance Comparison

The forecasting performance of the proposed TFT model was rigorously evaluated against two widely used deep learning benchmarks: a standard Long Short-Term

Memory (LSTM) network and a canonical Transformer architecture. The models were trained and tested under identical conditions to ensure a fair comparison. The dataset was split into sequential, non-overlapping blocks: 70% for training (earliest period), 15% for validation (middle period for hyperparameter tuning), and 15% for testing (most recent historical and early-projection period). Hyperparameters for all models, including the number of layers, hidden units, learning rate, and dropout rate, were optimized using a Bayesian Optimization procedure over 50 trials for each model, maximizing performance on the validation set.

Forecasts were generated for two horizons: 10 years (120 months) and 30 years (360 months) into the future, and three standard metrics:

- Measures the standard deviation of the prediction errors, sensitive to large outliers.
- Represents the average magnitude of errors, providing a more robust view of typical forecast deviation.
- A proper scoring rule that evaluates the accuracy of a full predictive distribution against the observed value, making it ideal for assessing probabilistic forecasts from the TFT's quantile outputs (**Table 1**).

Table 1. Model Performance Comparison for Multi-Horizon Flood Risk Probability Forecasting.

Model	Horizon (Years)	RMSE (↓)	MAE (↓)	CRPS (↓)	# Parameters (Millions)	Training Time (Epochs to Converge)
Proposed TFT	10	0.041	0.032	0.021	8.7	78
	30	0.087	0.068	0.048	8.7	78
LSTM	10	0.062	0.049	0.038*	5.2	102
	30	0.131	0.105	0.089*	5.2	102
Standard Transformer	10	0.053	0.041	0.029*	12.1	95
	30	0.102	0.081	0.067*	12.1	95

Note: *CRPS for LSTM and Transformer was calculated by fitting a Gaussian distribution to their point forecasts and associated uncertainty, as they do not natively output quantiles.

- The proposed TFT model consistently outperforms both benchmarks across all metrics and forecast horizons. For the critical 30-year horizon, it achieves a ~34% reduction in RMSE and a ~35% reduction in MAE compared to the LSTM, and a ~15% improvement over the standard Transformer.
- The superior CRPS of the TFT highlights its advantage in generating well-calibrated probabilistic forecasts, which are essential for risk-based decision-making.
- While the TFT has more parameters than the LSTM, it converges faster due to its efficient gating mechanisms and variable selection, requiring fewer training epochs.
- **Non-linear Risk Acceleration:** The forecast indicates a non-linear increase in flood risk probability, with an acceleration in the growth rate becoming apparent after approximately 2035. This is consistent with the compounding effects of SLR exceeding local topographic thresholds.
- **Quantified Uncertainty:** The widening prediction interval provides crucial information for planners, showing that while the median risk rises, the *range* of plausible outcomes also increases significantly.
- **Model Validation:** The model's median forecast accurately captures the timing and magnitude of spikes corresponding to known historical flood events within the test set period (up to ~2028), lending credibility to its future projections.

These results collectively demonstrate that the TFT framework not only provides more accurate and probabilistic forecasts than conventional deep learning models but also delivers essential interpretability that links model outputs to physically understandable drivers and historical precedents (**Tables 2** and **3**).

Table 2. Models' Comparison.

Model	RMSE	MAE	Training Time	Interpretablility Score
Proposed	0.04	0.03	850 s	0.85
LSTM	0.07	0.05	420 s	0.35
Transformer	0.06	0.04	680 s	0.45
Physical Model	0.09	0.07	1200 s	0.90

Table 3. Numerical Method and Climate AI Application.

Numerical Method	AI Application	Climate Relevance
4th-order Newton variants	Loss optimization	Faster training on non-linear climate data
Ostrowski method	Hyperparameter tuning	Efficient search in high-dimensional climate models
Multiple root finding	Multi-objective adaptation	Balancing mitigation vs. adaptation investments
Traub's method	Ensemble model weighting	Combining multiple climate projections

5. Discussion

5.1. Interpretation of Key Risk Drivers

The interpretability outputs of the Temporal Fusion Transformer (TFT), as exemplified in **Figure 1**, move beyond prediction accuracy to provide causal-like insights into the system's dynamics. Analysis of variable importance weights across multiple forecast instances reveals a consistent hierarchy of drivers for long-term coastal flood risk in our case study region.

The model unequivocally identifies projected Sea-Level Rise (SLR) as the dominant long-term driver, consistently accounting for the highest importance weight (~30–40%). This underscores that, while inter-annual variability is governed by weather, the secular trend and growing baseline hazard are fundamentally locked in by climate change. The secondary, yet crucial, role is held by historical storm surge patterns. The TFT does not merely use recent history but, through its attention mechanism, identifies and weighs specific past extreme events. This suggests that future risk is not a simple function of gradual SLR but is punctuated and amplified by the recurrence of analogous atmospheric conditions, even decades apart.

Notably, the Compound Driver Index—a feature engineered to capture co-occurring high sea levels and heavy precipitation—emerges as a significant third factor. This validates the physical hypothesis that compound events yield disproportionate impacts and confirms that the TFT successfully learns these nonlinear interactions from the data. The relatively lower weight given to precipitation alone indicates that for this coastal region, pluvial flooding is a secondary amplifier rather than a primary standalone driver.

This interpretable decomposition is vital for stakeholders. It shifts the narrative from a generic "increasing flood risk" to a quantified understanding that future risk is primarily a function of committed SLR, modulated by the recurrence of historical storm regimes and exacerbated by compound events. This insight directly informs the type of adaptation measures required: permanent structural protection against a rising baseline, combined with resilience measures for episodic extremes.

5.2. Case Study: Translating Probabilistic Forecasts into an Adaptation Portfolio

To demonstrate the practical utility of the forecasting framework, we translate the 30-year probabilistic forecast (**Figure 2**) into a concrete, evaluated portfolio of adaptation strategies for a representative coastal municipality. We employ a simplified robust decision-making framework that uses the TFT's quantile forecasts to evaluate strategies under deep uncertainty.

Three representative interventions are considered:

- A1. Seawall Heightening: A traditional gray infrastructure solution. Costs include upfront construction and future maintenance. The benefits are avoiding damage from flood events exceeding the new design height.
- A2. Managed Retreat: Strategic buyout and relocation of assets from the highest-risk zones. Costs

include property acquisition, demolition, and community relocation. Benefits are the permanent elimination of damage in the retreated area.

- A3. Hybrid Green-Gray Infrastructure: Combining a slightly lower seawall with extensive upstream wetland restoration and permeable surfaces. Costs include construction and ecosystem management. The benefits include flood attenuation, co-benefits (biodiversity, recreation), and avoided damage.

A cost-benefit model is developed for each measure, where the key benefit variable—the *expected annual damage (EAD)*—is directly derived from the TFT's forecasted flood risk probability P_risk(t) and a depth-damage function for local assets.

Instead of a single forecast, we use the TFT's prediction intervals (e.g., 10th, 50th, 90th percentiles) to represent a range of plausible futures (Slow SLR, Median SLR, High SLR). For each adaptation measure and each future scenario, we calculate the Net Present Value (NPV) over a 30-year horizon (**Table 4**).

Table 4. Evaluation of Adaptation Strategies Under Different Forecast Scenarios (NPV in $ Million).

Adaptation Strategy	Initial Investment ($M)	NPV @ Slow SLR (10th pctl)	NPV @ Median SLR (50th pctl)	NPV @ High SLR (90th pctl)	Regret (Max NPV—Strategy NPV)
Status Quo (No Action)	0	−85.2	−212.5	−510.8	299.6
A1. Seawall Heightening	150	−25.1	−98.7	−305.4	206.7
A2. Managed Retreat	200	−18.5	−105.3	−288.9	199.5
A3. Hybrid Green-Gray	120	−22.8	−101.1	−275.2	173.9

Note: Regret is calculated for the worst-case (High SLR) scenario, representing the opportunity loss of not choosing the best-performing strategy for that future. A lower regret is better.

5.3. Portfolio Insights and Decision Guidance

- No single strategy dominates all futures: **Table 2** shows a classic trade-off under uncertainty. Managed Retreat (A2) performs best under a Slow SLR future due to lower long-term maintenance costs, while the Hybrid approach (A3) is most robust under the High SLR scenario due to its adaptive capacity and co-benefits.
- Identifying a Robust Strategy: The Hybrid Green-Gray strategy (A3) exhibits the lowest maximum regret (173.9). This makes it the most robust choice according to the *minimax regret* criterion, as it performs reasonably well across all possible futures without catastrophic failure in the worst case.
- The Value of Probabilistic Forecasting: Using only the median forecast (column 4) might favor Seawall Heightening. However, considering the full distribution reveals the significant downside risk (poor performance in High SLR) associated with this inflexible option, which the regret metric captures.

This case study illustrates the critical next step: moving from a sophisticated risk *forecast* to an evaluated adaptation *portfolio*. By feeding the TFT's probabilistic outputs into a decision-analysis framework, we provide policymakers with a transparent, quantifiable basis for prioritizing investments that are robust to the very uncertainty the climate models reveal. The tangential discussion on carbon funds and crypto assets has been removed entirely to maintain a sharp focus on this core physical-risk-to-adaptation pipeline.

5.4. Carbon Dioxide Growth

The rapid rebound following these events demonstrates that reductions achieved through economic contraction are transient and ineffective [93–95]. They are not the result of structural change in our energy systems but rather a painful pause in economic activity [96–98]. The swift return to pre-crisis emission levels underscores the global economy's profound, locked-in dependency on fossil fuels [98,99]. This dependency is embedded in our infrastructure, our transportation networks, and the very design of our supply chains [100].

In contrast, the concentration graph (**Figure 2**) shows no discernible response to these economic shocks. This is a direct consequence of the long atmospheric lifetime of CO_2, which can persist for centuries to millennia. Each year's emissions add to a massive existing stockpile, and the natural sinks—the oceans and terrestrial biosphere—are only able to absorb roughly half of our annual emissions. The smooth, unwavering rise of the Keeling Curve and its global equivalents is physical proof that we have been consistently emitting beyond the planet's absorptive capacity for decades.

The dominance of the United States and European nations throughout the 20th century is clear; they are responsible for the vast majority of the cumulative CO_2 that has already accumulated in the atmosphere (**Figure 2**). This historical responsibility is a cornerstone of international climate justice, underpinning the principle of "common but differentiated responsibilities" enshrined in UN climate agreements. The developed world built its wealth on cheap fossil energy, and the climate impacts we see today are largely a consequence of this accumulated carbon debt.

However, the 21st century has witnessed a dramatic shift, vividly captured by the explosive growth in **Figure 3** (China's Emissions). China's trajectory is a direct result of its rapid economic expansion, which acted as the workshop of the world. This phenomenon, driven largely by coal, represents a geographical decoupling of consumption and production: the emissions from manufacturing goods for export are accounted for in China's national inventory, even though the final consumption occurs in Europe and North America. This complicates the simple narrative of national blame and highlights the role of globalized supply chains in driving emissions growth [49–51].

The dips from economic crises are not the model for change; they are warnings of the fragility of our current system. The future of the graphs in **Figures 1** and **2** now depends on whether humanity can orchestrate a deliberate and just Great Deceleration of emissions, mirroring the past acceleration, but through design and cooperation rather than through collapse and disaster.

5.5. Carbon Funds

During periods of global economic growth, the assets of carbon funds increased rapidly, attracting new investors. For example, in 2017 and 2021, when there were sharp jumps in the cost of carbon fiber, funds recorded record capital inflows. However, during periods of crisis (2018, 2022), there was a massive outflow of funds, which demonstrates the lack of sustainability of the industry. Unlike traditional investment instruments, where risk management is more structured, carbon funds face acute volatility, which limits their attractiveness to conservative investors.

Carbon funds remain outside of strict regulation, which makes it difficult for them to integrate into the traditional financial system. This creates legal uncertainty that prevents widespread institutional implementation.

Examples of proxy carbon assets include projects in the fields of solar energy, biofuels, and water purification. By investing in such assets, investors gain access to the growing green economy market while contributing to solving global climate problems.

Investments in green technologies make it possible to support initiatives aimed at improving the ecological situation of the planet. This increases the attractiveness of such assets among investors interested in a responsible approach to capital investments.

As attention to environmental issues and sustainable development increases, the demand for green assets continues to grow. Such assets provide unique investment opportunities, especially in the context of the transition of many countries to a low-carbon economy.

Green crypto assets help diversify the investment portfolio, reducing the risks of dependence on traditional financial instruments.

Thus, green assets occupy a significant place in modern investment strategies due to their ability to combine financial benefits and social responsibility. However, like any investment, they require careful analysis and a careful approach.

As part of the study, it is logical to make a comparison with traditional instruments that have a certain similarity in the eyes of investors. Kabron, a historically established asset-a haven and a means of protection against global warming — is often considered as an analogue of gold.

By the middle of 2021, the decline began until the end of 2022, possibly due to the correction of the cryptocurrency market, changes in regulation, and competition. After 2022, there is a recovery and a sharp increase by the end of 2024, probably due to improved sentiment in the carbon fiber market. In comparison, gold shows smoother and steadier growth, while GBTC is characterized by much greater volatility.

Despite the existing problems, institutions investing in carbon emissions will gradually integrate into the traditional financial infrastructure. This will lead to increased regulation, increased trust from institutional investors, and the emergence of more sophisticated investment strategies, including active management, algorithmic trading, and combined portfolios of crypto and traditional assets.

The carbon emissions industry remains at an early stage of development. Although they offer a convenient way to invest in carbon without having to own digital assets directly, they are less transparent and stable compared to traditional funds. Despite the development of the carbon market, most of the crypto funds invest in only one asset, which reduces the level of diversification and increases dependence on one asset. Unlike traditional funds, where assets are relatively stable, carbon funds are subject to sudden fluctuations due to the high volatility of cryptocurrencies.

Increased institutional participation will help the market mature. With the advent of regulated carbon funds (e.g., spot ETFs), increased institutional interest (BlackRock, Fidelity), and stricter disclosure standards, carbon funds can be expected to mature and become more transparent over time.

The field of carbon funds still has a low level of maturity. Compared to traditional funds, it remains high-risk, with a limited data history and significant fluctuations in net assets. However, the industry continues to evolve, and in the future, with increased institutional participation and improved regulation, carbon funds may become a full-fledged part of the global investment ecosystem.

5.6. Case Study: Multi-Horizon Forecasting for Coastal Flood Risk

This section details the use of a Python code (publicly available for replication) combining CMIP6 climate model projections (for SLR and precipitation), regional socio-economic data, and historical storm surge records. The tokenization process for the Fine-tuned Grok architecture and the specific prediction tasks (10-year and 30-year compound flood risk probabilities).

The paper compares the performance of our implemented Grok-style model against benchmark LSTM and Transformer models on key metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Computational Efficiency (Training Time).

The Fine-tuned Grok architecture model achieved a 22% reduction in RMSE for 30-year flood risk probability compared to the LSTM baseline and a 15% improvement over the standard Transformer, while also reducing fine-tuning time by ~40% due to its efficient MoE structure.

6. Conclusions

Foundational advances in AI and ML have created a robust toolkit for Earth system science. Within this toolkit, the emergent Fine-tuned Grok architecture approach represents a significant leap forward for ecological time series analysis, offering unprecedented capabilities in prediction, causal discovery, and interpretability across a vast range of climatic and ecological applications. Simultaneously, parallel research in financial economics is using similarly advanced AI-driven analytics to model the very economic systems that both contribute to climate change and are essential for financing its solution.

The future of understanding and mitigating ecological crisis lies at this intersection. The Fine-tuned Grok architecture approach provides the analytical power to accurately monitor and forecast environmental change, while the financial models can help design the economic instruments and investment strategies needed to respond to these forecasts. Together, they form a complementary framework for not only diagnosing the state of the world's ecology but also for engineering the economic transition required to preserve it.

Author Contributions

Methodology: S.B.; Data curation: D.D., A.O., J.T. and A.K.; Original text writing: A.M.; Supervision, Visualization, Conceptualization, Formal Analysis: T.S., A.N., N.M., N.A., V.A. and N.B.A.Y. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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