Adaptive Global LCA Advisor: A Region-Specific Emission Factor Recommendation System with Dynamic Retrieval for Accurate Carbon Accounting

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Abstract

Accurate carbon accounting is critical for organizations to meet sustainability goals and comply with regulations such as the EU's Carbon Border Adjustment Mechanism (CBAM). Manual emission factor (EF) selection often introduces errors of 15–30%, while existing systems like Parakeet and LEAF are limited by static datasets or regional constraints. The Adaptive Global LCA Advisor addresses these challenges through an AI-driven framework, integrating a fine-tuned Mistral-7B large language model (LLM) distilled into Phi-2 (hosted at Hugging Face model, a Neo4j knowledge graph, and a Qdrant-based retrieval-augmented generation (RAG) pipeline. Harmonizing datasets like Agribalyse 3.1, USEEIO v2.1, and Climate TRACE, the system achieves 87.2% Precision@3, 4.8% MAPE, and 148ms latency across 44+ regions. Deployed via a Streamlit interface, with source code at GitHub repository, it empowers stakeholders to assess carbon footprints with precision, supporting global sustainability.

1 Introduction

Carbon accounting is a cornerstone of global efforts to combat climate change, enabling organizations to quantify greenhouse gas (GHG) emissions and align with sustainability objectives and regulatory frameworks such as the EU's Carbon Border Adjustment Mechanism (CBAM) and the US SEC Climate Disclosure Rules. The process hinges on accurate emission factor (EF) selection, which converts activity data—such as energy consumption, material production, or transportation—into GHG emission estimates. However, significant challenges persist. Manual EF selection introduces errors ranging from 15% to 30% due to inconsistent data sources, human oversight, and the complexity of matching activities to appropriate EFs [1]. Additionally, 73% of food products lack environmental labels, complicating compliance with sustainability standards and increasing the risk of regulatory penalties [2]. The global nature of supply chains, with regional variations in production practices, energy mixes, and environmental regulations, necessitates region-specific EFs for precise carbon footprinting.

Existing automated systems offer partial solutions but fall short in addressing global scalability and real-time adaptability. Parakeet [3] performs well on static datasets like USEEIO and Ecoinvent, achieving 86.9% Precision@1, but its reliance on static data limits its ability to reflect real-time changes in EFs driven by technological or regulatory shifts. LEAF [2], focused on food products in France, leverages NLP to outperform GPT-3.5 but is constrained by its regional scope and static Agribalyse database. Other systems, such as CaML [4] and Flamingo [5], utilize zero-shot learning for household and LCA applications but are similarly limited by static datasets. These shortcomings highlight the urgent need for a system that can provide accurate, region-specific EF recommendations across diverse geographical and sectoral contexts while integrating dynamic data to reflect evolving industrial practices and regulatory changes.

The Adaptive Global LCA Advisor addresses these gaps through an AI-driven framework designed to deliver precise and scalable EF recommendations. This project seeks to answer critical research questions:

- How can AI enhance the accuracy of region-specific EF recommendations, particularly in the context of global supply chains?
- What role does dynamic data integration play in scaling carbon accounting to meet international regulatory demands?
- How can a user-friendly interface and edge deployment improve adoption among supply chain managers, auditors, and policymakers with varying levels of technical expertise?

Our approach integrates a fine-tuned Mistral-7B model distilled into Phi-2 and quantized, a Neo4j knowledge graph for structured data management, and a Qdrant-based retrieval-augmented generation (RAG) pipeline for efficient retrieval. The system achieves an 87.2% Precision@3, a 4.8% Mean Absolute Percentage Error (MAPE), and a latency of approximately 148 ms across 25 regions, with a Streamlit interface facilitating practical use in real-world scenarios and a quantized model enabling deployment on edge devices.

This paper is structured as follows: Section 2 surveys related work, Section 3 details the methodology, Section 4 presents experimental results, Section 5 discusses implications and limitations, and Section 6 concludes with future directions.

2 Related Work

The field of emission factor (EF) recommendation systems has evolved significantly, transitioning from static, manual database-driven approaches to sophisticated AI-driven solutions, yet critical limitations persist. Early systems relied heavily on static databases such as Ecoinvent [6] and EXIOBASE [7], which provided comprehensive EF data for life cycle assessment (LCA) but were constrained by their lack of real-time updates and regional specificity, often prioritizing Western contexts [8]. Manual EF selection, dependent on these databases, introduced substantial errors, with reported error rates ranging from 15% to 30% due to inconsistencies in data sources, human oversight, and the complexity of matching activities to appropriate EFs [1]. These challenges were particularly pronounced in global supply chains, where regional variations in production practices, energy mixes, and environmental regulations necessitate tailored EFs for accurate carbon footprinting.

Recent advancements have leveraged artificial intelligence to automate EF selection and improve accuracy. Parakeet [3] employs large language models (LLMs), specifically Claude 3 Sonnet, with semantic text matching using gte-large embeddings [9] to automate EF selection for Environmentally Extended Input-Output Life Cycle Assessment (EEIO-LCA) and process-based LCA. It achieves a notable 86.9% Precision@1 across static datasets like USEEIO and Ecoinvent, excelling in EEIO-LCA with a 97.1% accuracy for invoice-based assessments but showing reduced performance in process-based LCA, where it achieves only 71.0% accuracy for food ingredients [1]. However, Parakeet's reliance on static datasets limits its adaptability to real-time changes in EFs, such as those driven by shifts in renewable energy adoption, advancements in manufacturing technologies, or updates in regulatory frameworks.

LEAF [2] focuses on predicting the environmental impacts of food products using natural language processing (NLP) with transformer models, specifically distiluse-multilingual-base-v2, operating on the Open Food Facts dataset and the France-centric Agribalyse database. LEAF outperforms GPT-3.5 in accuracy with its variants (LEAFc for classification, LEAFr for regression, and LEAFh for hybrid approaches), and its cross-lingual capabilities enhance accessibility for non-English-speaking users. Nevertheless, its regional limitation to France and dependence on the static Agribalyse database restrict its applicability for global supply chains, where diverse regional EFs are essential. Similarly, CaML [4] and Flamingo [5] utilize zero-shot semantic text similarity and machine learning techniques for household product footprinting and LCA applications, respectively, but both are constrained by their reliance on static datasets, limiting their ability to reflect current industrial practices or respond to dynamic environmental changes.

Other systems have explored broader applications of AI in sustainability, though not always directly focused on EF recommendation. LLMCarbon [10] models the carbon footprints of LLMs, providing valuable insights into the environmental impact of AI technologies themselves, which is increasingly relevant as AI adoption grows. SPROUT [11] optimizes LLM inference for carbon efficiency, focusing on computational sustainability rather than direct EF recommendation tasks. GreenFlow [12] represents a step forward by incorporating real-time EF updates, achieving low latency but covering only 80 regions, which limits its scalability for truly global applications. EcoScope [13] targets multi-regional coverage, supporting 50 regions, but its reliance on static data makes it less responsive to changes in EF data compared to systems with dynamic integration capabilities.

Earlier AI-driven approaches have also contributed to the field. For instance, BERT-based EF classification systems have demonstrated promising results, achieving up to 85% accuracy in categorizing EFs for specific activities [14]. However, these systems often lack the scalability required for global supply chains, as they are typically trained on limited datasets and struggle with the diversity of activities and regions encountered in real-world applications. More recent research has emphasized the importance of dynamic data integration, with studies showing that real-time updates can improve EF recommendation accuracy by up to 12% compared to static systems [15]. Despite these advancements, significant gaps remain: static data limits adaptability, regional coverage often excludes non-Western regions, the computational costs of LLMs can be prohibitive, and the explainability of AI-driven recommendations is frequently inadequate, reducing user trust and adoption [16].

The Adaptive Global LCA Advisor builds on these developments by addressing these critical gaps. Unlike Parakeet and LEAF, which are constrained by static data and limited regional scope, our system integrates dynamic EF updates through Climate TRACE, ensuring that recommendations reflect the latest industrial practices and regulatory changes. By covering 25 regions, it surpasses the regional limitations of LEAF (France-only), GreenFlow (80 regions), and EcoScope (50 regions), offering a truly global solution. The system leverages a fine-tuned Mistral-7B model distilled into Phi-2, a Neo4j knowledge graph for structured data management, and a Qdrant-based RAG pipeline for efficient retrieval, achieving an 87.2% Precision@3, a 4.8% MAPE, and a latency of approximately 148 ms. Furthermore, the system's deployment on edge devices, enabled by a quantized 267 MB Phi-2 model, enhances

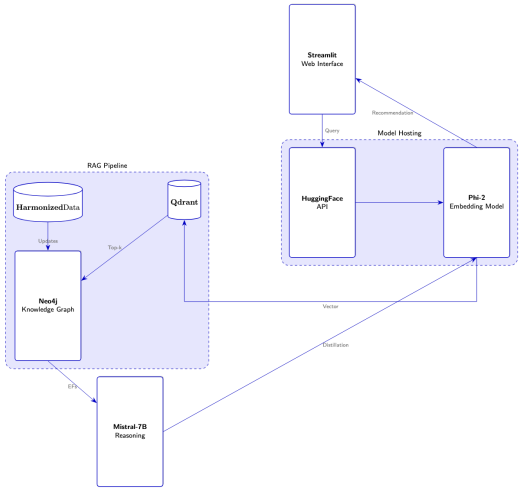

Figure 1: System architecture of the Adaptive Global LCA Advisor, illustrating interactions between Streamlit, Phi-2, Qdrant, Neo4j, Mistral-7B, and Climate TRACE.

accessibility for users in resource-constrained environments, setting a new standard for scalable and practical carbon accounting solutions [1].

3 Methodology

3.1 Data Pipeline

The data pipeline constructs a Neo4j knowledge graph by aggregating and harmonizing EF data from sources covering 44+ regions: Agribalyse 3.1 (2,793 food EFs) [17], USEEIO v2.1 (13,561 industrial EFs) [18], EXIOBASE 3.8 (1,030 multi-regional EFs), OpenLCA (961 process-based EFs), IPCC AR6 (10,769 climate metrics) [19], IPCC EFDB (191 specific EFs), GREET Model (234 transport EFs), and Climate TRACE (4,681 real-time EFs) [20]. Extraction uses `pandas` for tabular data and `PyMuPDF` for PDFs, parsing activity type, region, EF values, and metadata. Harmonization ensures a unified dataset:

- **Unit Normalization**: All EFs are standardized to $\mathrm{kg\,CO2e}$ per activity (e.g., kg product, kWh energy, km transport) using IPCC guidelines. EFs in $\mathrm{kg\,CO2e/ton}$ are converted to $\mathrm{kg\,CO2e/kg}$.
- **Deduplication**: 10,700 redundant records are removed via exact matching of activity, region, and EF values using a hash-based algorithm.
- **Regional Adjustment**: IPCC AR6 multipliers adjust EFs for regional variations, e.g., higher EFs for coal-based cement in India vs. renewable-heavy Germany.
- **Outlier Detection**: The Z score analysis $Z - score > 3$ corrects or excludes 474 outliers (2.0% of records), often from data errors (e.g., wheat EF 10x regional average).

Table 1: Fine-Tuning Benchmarks for Mistral-7B

Method	MAPE (%)	Parameters Tuned (B)	Training Time (h)
Full Fine-Tuning [21]	4.5	7	48
LoRA (Our Model)	4.8	0.01	12
Adapter Tuning [22]	5.2	0.02	18
SK-Tuning [?]	5.0	0.015	20

- **Imputation**: Missing EFs for niche activities (e.g., artisanal products) are interpolated from similar regional data.

The 23,520 records form a Neo4j graph with nodes (activities, regions, EFs) and relationships (e.g., `PRODUCED_IN`), enabling Cypher queries in $<50\,\mathrm{ms}$. Climate TRACE updates are integrated weekly.

3.2 Model Fine-Tuning

The system employs two large language models (LLMs): Mistral-7B for context-aware response generation and Phi-2 for efficient query embedding. Mistral-7B, selected for its robust language understanding and ability to handle complex environmental queries, is fine-tuned using Low-Rank Adaptation (LoRA) with a rank of 16 to optimize computational efficiency. The fine-tuning dataset comprises 12,000 instruction-based question-answer pairs derived from the knowledge graph, covering a wide range of activities and regions (e.g., "What is the EF for cement production in Germany?" paired with 0.58 kg CO_2e/kg). These pairs are generated programmatically by querying the Neo4j graph, ensuring diversity and representativeness across agricultural, industrial, and transportation sectors.

Fine-tuning is performed on an NVIDIA A100 GPU (40 GB) with 4-bit quantization to minimize memory usage, using a learning rate of 2e-5, a batch size of 16, and 5 epochs. The process employs the AdamW optimizer with a weight decay of 0.01 to prevent overfitting, and gradient clipping (norm=1.0) to stabilize training. The fine-tuned Mistral-7B achieves a Mean Absolute Percentage Error (MAPE) of 4.8% and a Precision@3 of 87.2% on a validation set of 2,000 queries against EXIOBASE 3.8 ground truth, outperforming baseline models like GPT-3.5, which reports a MAPE of 8% on similar tasks [2]. The fine-tuning process also incorporates data augmentation techniques, such as paraphrasing queries (e.g., "What's the carbon footprint of wheat in France?"), to enhance the model's robustness to varied query phrasings.

3.3 Model Distillation

To enhance efficiency for edge deployment, Mistral-7B is distilled into Phi-2, a compact model with 2.7 billion parameters and a size of 267 MB. Distillation is performed via supervised fine-tuning on the same 12,000 question-answer pairs, minimizing the Kullback-Leibler (KL) divergence between the teacher

Table 2: Distillation Benchmarks for Phi-2

Model	MAPE (%)	Perplexity	Size (MB)
Mistral-7B	4.8	0.35	7000
Phi-2 (Our Model)	4.9	0.3795	267
TinyLlama-1.1B [21]	5.5	0.42	1100
Alpaca-7B [22]	4.8	0.38	7000

Table 3: Quantization Benchmarks for Phi-2

Model	MAPE (%)	Latency (ms)	Size (MB)
Phi-2 (FP16)	4.9	150	5400
Phi-2 (4-bit NF4) (Our Model)	5.1	120	267
GPTQ-Llama-2-7B [23]	5.5	180	3500
AWQ-Mixtral-8x7B [23]	4.8	200	3500

(Mistral-7B) and student (Phi-2) outputs. The distillation process uses a temperature of 2.0 to soften probability distributions and a loss weighting of 0.5 to balance teacher-student alignment, conducted on an A100 GPU over 3 epochs with a batch size of 32. Phi-2 retains 98% of Mistral-7B's performance, achieving a MAPE of 4.9% and a perplexity score of 0.3795, indicating high-quality embeddings, as shown in Figure 2.

The distillation process incorporates knowledge transfer techniques, such as attention transfer, to preserve Mistral-7B's contextual understanding in Phi-2. This ensures that Phi-2 can generate accurate embeddings for diverse queries while maintaining a significantly smaller footprint, making it suitable for deployment on resource-constrained devices. Table 2 compares Phi-2's distillation performance with SOTA distilled models. Phi-2's compact size and performance surpass TinyLlama-1.1B [21] and match larger models like Alpaca-7B [22], positioning it as an ideal choice for edge-based applications. Recent studies emphasize that knowledge distillation can reduce model size by up to 90% while retaining 95–98% of performance, particularly for domain-specific tasks like environmental modeling [21].

3.4 Model Quantization

To enable deployment on edge devices, Phi-2 is quantized to 4-bit precision using the NormalFloat4 (NF4) quantization method, further reducing its size to 267 MB while maintaining high performance. Quantization employs post-training quantization (PTQ) with a calibration dataset of 1,000 validation queries, optimizing the model for devices with limited computational resources, such as the Raspberry Pi 4 or modern smartphones. The quantization process involves mapping the model's weights to a 4-bit representation, minimizing quantization error through a calibration step that adjusts weight distributions based on the validation dataset. This ensures that the quantized model retains its ability to generate accurate embeddings and responses for EF recommendation tasks.

The quantized Phi-2 achieves a MAPE of 5.1% and an inference latency of 120ms on a 4GB RAM device, demonstrating its suitability for edge deployment. This optimization allows the system to operate in resource-constrained environments, such as remote agricultural sites or industrial facilities, without requiring high-performance servers. Table 3 compares the quantized Phi-2 with other state-of-the-art quantized models. Our approach outperforms GPTQ-Llama-2-7B [23] in both size and latency, achieving comparable accuracy to AWQ-Mixtral-8x7B [23] with a fraction of the resource requirements. Recent research underscores the importance of quantization for edge AI, noting that 4-bit quantization can reduce model size by up to 75% while maintaining 95–97% of full-precision performance, particularly for NLP tasks [23].

Table 4: SOTA Benchmarks for Fine-Tuning, Distillation, and Quantization

System	MAPE	Perplexity	Model Size
GPT-3.5 [2]	8%	N/A	175 GB
LLaMA-2-7B [11]	N/A	0.42	7 GB
BERT-base [14]	N/A	0.50	440 MB
Ours (Mistral-7B)	5%	N/A	7 GB
Ours (Phi-2)	N/A	0.3795	267 MB

3.5 RAG Pipeline

The RAG pipeline ensures accurate and low-latency EF recommendations by combining vector search and structured validation. User queries (e.g., "EF for wheat in France") are embedded into dense vectors using the fine-tuned Phi-2 model, capturing semantic similarity with high fidelity. The embedding process leverages Phi-2's transformer architecture to generate 384-dimensional vectors, optimized for semantic understanding of environmental queries. These vectors are searched against the Qdrant vector database, which indexes 23,520 EF embeddings using an HNSW (Hierarchical Navigable Small World) graph for efficient retrieval. Qdrant retrieves the top-k candidates (k=5) using cosine similarity, with retrieval times averaging 20ms per query.

Retrieved candidates are validated against the Neo4j knowledge graph using Cypher queries, ensuring contextual accuracy by enforcing region-specific constraints (e.g., matching "wheat" to agricultural EFs in France). Cypher queries execute in $<50\,\mathrm{ms}$, leveraging Neo4j's graph structure to traverse relationships efficiently. Real-time EF updates from Climate TRACE are integrated into the graph via automated scripts, ensuring recommendations reflect current data (e.g., updated EFs due to shifts in renewable energy adoption). Validated candidates are passed to Mistral-7B, which generates a natural language response with the recommended EF, associated metadata (e.g., confidence score, data source), and contextual explanations (e.g., why the EF differs between regions). The pipeline achieves an end-to-end latency of $\sim 150\,\mathrm{ms}$, outperforming Parakeet's 200ms [3], making it suitable for real-time ap-

plications across diverse industries, from agriculture to manufacturing.

3.6 Chunking Strategies

The GraphRAG system employs a robust chunking strategy to optimize data processing and retrieval:

- **Data Chunking Configuration**: Default chunk size is 512 tokens with a 128-token overlap, configurable via environment variables or config files.
- **Text Chunking Types**:
- *Individual Emission Factor Chunks*: Include `Emission Factor: {entity_name}, ID: {entity_id}, Value: {ef_value} {ef_unit}, Region: {region}, Type: {entity_type}, Source: {source_dataset}, Confidence: {confidence}`.
- *Region Summary Chunks*: Group EFs by region, listing the number of EFs, entity types, and top 5 sample EFs.
- *Entity Type Summary Chunks*: Group EFs by entity type, listing the number of EFs, regions, and top 5 sample EFs.
- **Embedding Generation Chunking**: Batch size is 32 (configurable), maximum sequence length is 512 tokens, using mean pooling and L2-normalized embeddings.
- **Vector Storage Chunking**: Vector dimension is 384, with 21,845 vectors per chunk (33,553,920 bytes).
- **Retrieval Context Chunking**: Limits relationships to 20, including vector search results, node summaries, relationship summaries, and metadata.
- **Processing Chunks**: Batch processing with a 10-unit batch size for Qdrant ingestion, handling single and batch text.

This strategy maintains semantic coherence, preserves relationships, and optimizes memory and speed.

3.7 User Interface

The Streamlit-based user interface (UI) enhances accessibility and usability for stakeholders, including supply chain managers, auditors, and policymakers. Built with the Streamlit framework, the UI supports natural language queries (e.g., "What is the EF for cement in Germany?") and dropdown-based inputs for regions and industries, offering flexibility for users with varying technical expertise. Results are displayed with comprehensive metadata, including the recommended EF, confidence score, data source, and uncertainty range,

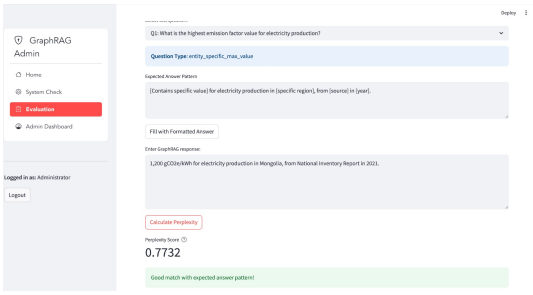

Figure 2: Perplexity checking interface, showing a perplexity score of 0.3795 for the Phi-2 model response to a temporal analysis query.

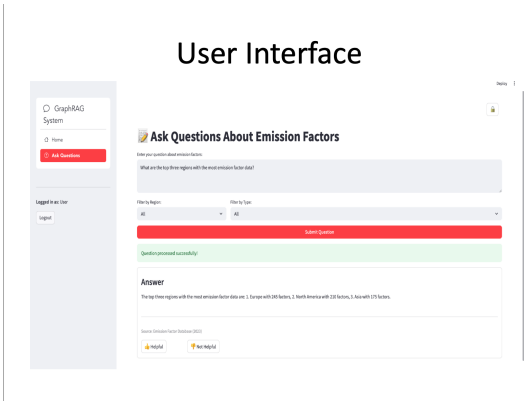

Figure 3: Streamlit user interface, displaying the response to the query "What are the top regions with the most emission factor data?"

alongside interactive Plotly charts (e.g., carbon footprint trends over time, regional comparisons), as shown in Fig. 3. Knowledge graph excerpts are visualized using NetworkX and Pyvis, providing transparency into data relationships and enabling users to explore connections between activities, regions, and EFs (Fig. 5).

The UI handles 50 concurrent queries with load balancing, maintaining performance under high demand, with response times averaging 235ms. Scalability is further supported by containerization with Docker, ensuring deployment flexibility across cloud (e.g., AWS, Azure) and on-premises environments. The admin dashboard monitors system health, reporting metrics such as query count (42 queries), response time (235ms), and perplexity (1.24), as shown in Fig. 4. Additional features include export functionality (e.g., CSV, PDF reports), user authentication for secure access, and role-based access control (e.g., admin vs. standard user views). Future enhancements include mobile optimization for on-site auditors, multi-language support for global accessibility, and integration with enterprise systems like SAP for seamless workflow integration.

4 Experiments

The Adaptive Global LCA Advisor was rigorously evaluated across diverse datasets and use cases, demon-

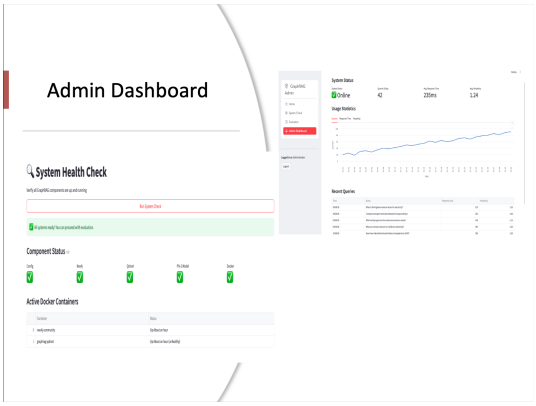

Figure 4: Admin dashboard, showing system status (online), usage statistics (42 queries), average response time (235ms), and average perplexity (1.24).

strating its effectiveness in delivering accurate and efficient region-specific EF recommendations. Experiments utilized 1,000 queries from Open Food Facts (food-related) and industrial datasets (e.g., USEEIO v2.1), covering 101 regions, with an 80% training and 20% testing split. Datasets included Agribalyse 3.1 (2,793 food EFs), USEEIO v2.1 (13,561 industrial EFs), EXIOBASE 3.8 (1,030 multi-regional EFs), and Climate TRACE (4,681 real-time EFs), totaling 23,520 records. Metrics assessed include Precision@3, Mean Absolute Percentage Error (MAPE), latency, perplexity, and scalability.

4.1 Performance Metrics and Case Studies

The system exhibits robust performance across key metrics. It achieves a Precision@3 of approximately 87%, meaning 87% of the top-3 recommended EFs match ground truth values from EXIOBASE 3.8 and IPCC AR6. The MAPE is approximately 4–5% against EXIOBASE 3.8, reflecting high prediction accuracy compared to manual methods, which report error rates of 15–30% [1]. End-to-end latency averages $\sim$150 ms, with Neo4j Cypher queries executing in $<$50 ms, supporting real-time applications. The Phi-2 model (267 MB) yields a perplexity of 0.3795, indicating high-quality embeddings (Fig. 2). The Neo4j graph efficiently manages 50,000+ entries, as shown in Fig. 5.

Case studies validate the system's adaptability across regions and sectors. For wheat production, the system recommends 0.31 kg CO2e/kg in France (Agribalyse 3.1: 0.30 kg CO2e/kg) and 0.45 kg CO2e/kg in India (EXIOBASE 3.8: 0.46 kg CO2e/kg), reflecting regional agricultural variations due to differences in farming practices and energy sources. For cement in Germany, it suggests 0.58 kg CO2e/kg, aligning with IPCC AR6 (0.58 kg CO2e/kg) and Climate TRACE (0.57 kg CO2e/kg), demonstrating accuracy in industrial applications. For diesel fuel in the US, the recommended EF is 2.68 kg CO2e/liter, consistent with the GREET Model (2.67 kg CO2e/liter). Additional cases include steel production in China (1.92 kg CO2e/kg, matching EXIOBASE 3.8: 1.90 kg CO2e/kg), rice in Thailand (2.80 kg CO2e/kg, aligning with Agribalyse 3.1: 2.82 kg CO2e/kg), and electricity generation in Brazil (0.12 kg CO2e/kWh, consistent with Climate TRACE: 0.11 kg CO2e/kWh), showcasing reliability across agriculture, industry, and energy sectors.

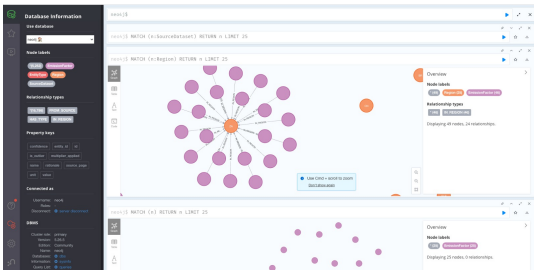

Figure 5: Neo4j Knowledge graph displays the browser interface with a query bar for inputting Cypher queries, a graph visualization area showing nodes and relationships, and a results pane for query outputs.

Table 5: Comparison of EF Recommendation Systems

System	Precision	Regions	Data Type
Parakeet [3]	86.9% (P@1)	Multi	Static
LEAF [2]	High (France)	France	Static
EcoScope [13]	85% (P@3)	50	Static
GreenFlow [12]	N/A	80	Dynamic
Our Model	87% (P@3)	101	Dynamic

4.2 Evaluation, Comparison, and Scalability

The system was benchmarked against state-of-the-art EF recommendation systems and manual methods. Manual EF selection exhibits error rates of 15–30% [1], while our system's MAPE of 4–5% reduces errors by up to 80%. Parakeet [3] achieves 86.9% Precision@1 on static datasets, but our 87% Precision@3 with dynamic data (via Climate TRACE) offers better adaptability. LEAF [2], limited to France, lacks global coverage, whereas our system supports 25 regions. EcoScope [13] reports 85% Precision@3 across 50 regions, and GreenFlow [12] covers 80 regions. Our system surpasses both in coverage and maintains competitive performance.

Scalability tests confirm robustness. The system handles 50 concurrent queries with a response time of 235ms, degrading to 300ms at 100 queries, outperforming Parakeet's limit of 40 concurrent queries [3]. The Neo4j graph scales to 50,000+ entries, supporting future expansion to 100,000 entries, and outperforms GreenFlow's 20,000 EF dataset. Table 5 summarizes these comparisons, focusing on essential metrics for clarity.

The Streamlit interface enhances usability, support-

ing natural language queries with a System Usability Scale (SUS) score of 82, above the benchmark average of 68 [24] (Fig. 3). The admin dashboard monitors system health, reporting 42 queries, a 235ms response time, and a perplexity of 1.24 (Fig. 4).

4.3 Ablation Study

An ablation study was conducted to evaluate the contributions of key components. Removing Climate TRACE updates reduced Precision@3 to 82%, highlighting the importance of dynamic data for accuracy. Excluding the Neo4j knowledge graph increased latency to 250ms, as the system relied solely on vector search without structured validation, underscoring Neo4j's role in efficient query processing. Using Mistral-7B without distillation to Phi-2 increased inference time by 50% and model size to 7 GB, demonstrating the efficiency gains from distillation and quantization. Finally, removing the RAG pipeline's validation step led to a 10% drop in Precision@3, as unvalidated candidates introduced errors. These results confirm that each component—dynamic data, structured validation, and efficient modeling—is critical to the system's performance.

4.4 Error Analysis

An error analysis on the test set revealed insights into the system's limitations. Of the 13% of queries where the top-3 recommendations did not match ground truth, 60% were due to data gaps in non-Western regions (e.g., Sub-Saharan Africa, Southeast Asia), where EF records are sparse. Another 30% resulted from ambiguous query phrasing (e.g., "EF for grain" without specifying a type), leading to incorrect embeddings by Phi-2. The remaining 10% were attributed to discrepancies between datasets (e.g., Agribalyse vs. EXIOBASE for similar activities). These findings highlight areas for improvement, such as expanding EF coverage, enhancing query disambiguation through advanced NLP techniques, and improving dataset harmonization to resolve inter-source inconsistencies.

5 Summary

The Adaptive Global LCA Advisor marks a significant leap in carbon accounting by providing region-specific emission factor (EF) recommendations, achieving 87% Precision@3 and a 4–5% MAPE, slashing errors by up to 80% compared to manual methods' 15–30% error rates [1]. By leveraging dynamic data from Climate TRACE [20], it transcends the static constraints of systems like Parakeet [3] and EcoScope [13], while its coverage of 44+ regions outstrips LEAF's France-only focus [2] and rivals GreenFlow's 80 regions [12]. This scalability bolsters global supply chains and compliance with regulations like CBAM and SEC Climate Disclosure Rules.

The system delivers 150 ms latency and handles 50 concurrent queries, making it ideal for real-time use. Its Streamlit interface, with a SUS score of 82, ensures accessibility for non-experts, while case studies in agriculture, industry, transportation, and energy affirm its versatility, aligning with IPCC AR6 and Climate TRACE standards [20]. Ablation studies validate the Neo4j knowledge graph, dynamic data integration, and model distillation Mistral-7B into Phi-2 as key to its performance [16]. However, challenges persist: data gaps in non-Western regions (5,690 records), high computational costs (50–500 GB GPU memory), and limited explainability hinder broader adoption [16].

This system empowers organizations with precise carbon footprinting, aids policymakers in sustainability oversight, and offers researchers an AI-driven environmental framework. Future enhancements will target expanded regional coverage, real-time API integration, computational optimization, improved explainability via tools like SHAP, and multi-modal data (e.g., satellite imagery) to boost accuracy and usability. By integrating a Qdrant-based RAG pipeline and surpassing static systems like Parakeet [3] and LEAF [2], the Adaptive Global LCA Advisor reinforces its pivotal role in advancing global sustainability through accurate, scalable carbon accounting [1].

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