CARBONOSPHERE-AI: A Planetary Digital Twin for Adaptive Carbon Sink Management and Climate Regulation

Aniket Agarwal
Bachelor of Technology, Computer Sciences
Amity University, Punjab, India

Abstract—Climate change mitigation requires innovative approaches beyond traditional emission reduction strategies. CARBONOSPHERE-AI introduces a self-evolving planetary digital twin designed to model, simulate, and actively manage Earth's carbon sinks. The system integrates Graph Neural Networks (GNNs) to model inter-regional carbon fluxes, Physics-Informed Neural Networks (PINNs) for constraint adherence, and Proximal Policy Optimization (PPO) reinforcement learning to optimize intervention strategies. Real-world data from ERA5 NetCDF and multi-greenhouse gas layers (CO_2, CH_4, N_2O) enhance model fidelity. This paper presents the architecture, methodology, and environmental significance of CARBONOSPHERE-AI, highlighting its potential to support ecosystem restoration, climate policy, and sustainable development.

Index Terms—Digital twin, carbon sinks, climate change, reinforcement learning, graph neural networks, environmental AI, PPO, PINNs

I. Introduction

Global climate challenges demand advanced solutions that go beyond emissions monitoring. While existing climate models focus primarily on predictive analytics, they often overlook dynamic intervention strategies for carbon sinks, such as forests, oceans, and soils. CARBONOSPHERE-AI addresses this gap by providing a live, adaptive digital twin of Earth capable of learning, predicting, and controlling carbon fluxes in real time.

II. Problem Statement and Motivation

Atmospheric CO_2, CH_4, and N_2O levels continue to rise, posing risks to ecosystems, human health, and global stability. Conventional climate models do not account for the complex interactions between carbon sinks and anthropogenic activity in a dynamic manner. There is a need for a system that:

- Models carbon absorption and release across multiple ecosystems.
- Predicts tipping points in forest, soil, and ocean carbon storage.
- Suggests optimal interventions for ecosystem restoration and carbon sequestration.

III. Related Work

Prior research has explored AI in climate modeling [1], [2], digital twins for environmental monitoring [3], and GNNs for geospatial data [4]. Reinforcement learning has been applied to optimize energy systems and emission controls [5]. CARBONOSPHERE-AI uniquely integrates these approaches to form a unified planetary carbon twin with actionable intelligence.

IV. Methodology

The CARBONOSPHERE-AI architecture combines data ingestion, modeling, intervention optimization, and visualization.

A. Data Sources

- ERA5 NetCDF: Real-world oceanic and atmospheric data.
- Multi-GHG Layers: CO_2, CH_4, N_2O for accurate carbon modeling.
- Forest and Soil Maps: Global satellite and GIS data.

B. Graph Neural Networks (GNNs)

Carbon sinks and their interactions are modeled as a graph:

- Nodes: Forests, oceans, soils.
- Edges: Carbon flux between regions.

```
from torch_geometric.nn import GCNConv

class EarthGNN(torch.nn.Module):
    def __init__(self):
        super().__init__() self.conv1 =
        GCNConv(3, 16) self.conv2 =
        GCNConv(16, 1)
    def forward(self, x, edge_index): x = self.conv1(x,
        edge_index).relu() return self.conv2(x, edge_index)
```

C. Physics-Informed Neural Networks (PINNs)

To ensure predictions respect physical laws of carbon flux and ocean chemistry, PINNs constrain outputs with real-world physics.

D. Reinforcement Learning (PPO)

The system uses PPO to optimize interventions:

- State: Current carbon levels, GNN outputs.
- Action: Suggested interventions like reforestation or soil enrichment.
- Reward: Maximized carbon absorption while minimizing cost.

```
action = policy(state) next_state, reward =
environment.step(action) policy.update(state, action, reward)
```

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E. Visualization

Interactive 3D visualizations are implemented with Plotly Dash:

- Node color indicates carbon flux.
- Real-time simulation of interventions.

```
import plotly.graph_objects as go fig =
go.Figure(data=[go.Scatter3d( x=positions_x,
y=positions_y, z= positions_z,
        mode='markers', marker=dict(size=5,
        color=carbon_flux, colorscale='Viridis')
)]) fig.show()
```

V. Experiments and Implementation

The model has been tested on global datasets:

- Training the GNN on multi-GHG data to predict regional carbon flux.
- PPO agents simulated intervention strategies over decadal scales.
- Visualizations validated against historical carbon absorption trends.

Software stack:

- Python 3.11
- PyTorch, PyTorch Geometric
- TensorFlow for PINNs
- Plotly Dash for visualization
- NetCDF4 for data ingestion

VI. Results and Discussion

CARBONOSPHERE-AI enables:

- Identification of carbon sink tipping points.
- Optimal global reforestation and oceanic carbon sequestration strategies.
- Interactive policy simulations.

3D simulations and PPO training loops provide decisionmakers with actionable insights for climate mitigation.

VII. Environmental Impact

By actively managing carbon sinks:

- Atmospheric CO_2 levels can be stabilized.
- Ecosystem restoration is promoted.
- Climate tipping points are delayed or prevented.

VIII. Future Work

- Integrate biodiversity and hydrological cycles.
- Real-time satellite and sensor data assimilation.
- High-resolution regional twins for local policy decisions.
- Explore multi-agent reinforcement learning for cooperative global interventions.

IX. Conclusion

CARBONOSPHERE-AI represents a paradigm shift in climate modeling. By integrating AI, physics, and environmental data, it provides a live, adaptive platform for carbon sink management, ecosystem restoration, and policy simulation. This approach enables proactive, informed climate intervention strategies that can significantly impact environmental sustainability.

References

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[5] Schulman, J., et al., "Proximal Policy Optimization Algorithms," *arXiv:1707.06347*, 2017.

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CARBONOSPHERE-AI: A Self-Evolving Planetary Digital Twin for Carbon Sink Intelligence and Greenhouse Gas Regulation

Aniket Agarwal
Bachelor of Technology, Computer Sciences Amity University, Punjab, India

Abstract

Climate change is fundamentally a problem of imbalance between greenhouse gas emissions and the Earth's natural capacity to absorb them. While emissions monitoring has advanced rapidly, the intelligence required to understand, protect, and optimize carbon sinks remains limited.

This work introduces *CARBONOSPHERE-AI*, a self-evolving planetary-scale digital twin designed to model, predict, and govern global carbon sinks under physical, ecological, economic, and policy constraints. The system integrates graph intelligence, physics-informed learning, neuromorphic memory, reinforcement learning, and interactive visualization into a unified cognitive framework.

CARBONOSPHERE-AI shifts climate modeling from static prediction to adaptive reasoning, enabling long-term carbon regulation strategies that are scientifically grounded, economically feasible, and environmentally sustainable.

Introduction

Climate change discussions traditionally focus on emissions: how much carbon dioxide is released and how emissions can be reduced. However, emissions represent only half of the climate equation. The other half—carbon sinks—determines whether the planet can stabilize itself.

Carbon sinks such as forests, oceans, soils, wetlands, and phytoplankton absorb a significant portion of atmospheric carbon dioxide. These systems are dynamic, slowreacting, and capable of sudden collapse. Ignoring their behavior leads to incomplete and often misleading climate strategies.

CARBONOSPHERE-AI is designed to address this gap by placing carbon sinks at the center of climate intelligence.

Why This Project Is Needed

Limitations of Existing Climate Models

Most existing climate tools suffer from three major limitations:

- They operate in isolation, separating ecology, economics, and policy.
- They are static, relying on predefined scenarios rather than learning systems.
- They fail to capture long-term memory and delayed responses of carbon sinks.

These limitations make it difficult to design robust, future-proof climate strategies.

Shift from Emission Control to Sink Intelligence

Emission reduction alone cannot stabilize the climate without strengthening natural and engineered carbon sinks. CARBONOSPHERE-AI introduces a sink-centric approach, treating carbon absorption systems as controllable, optimizable, and governable assets.

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Core Research Idea

The central research idea is to treat Earth's carbon cycle as a living, learning system rather than a static physical process.

This is achieved by:

- Representing Earth as a graph-based digital twin
- Embedding physical laws directly into AI models
- Using memory-driven neural systems to capture long-term dynamics
- Allowing artificial agents to actively design carbon sink strategies
- Simulating economic and policy feasibility alongside environmental impact

Planetary Digital Twin Architecture

Graph-Based Representation of Earth

The planetary digital twin represents Earth as a graph:

- Nodes represent forests, ocean basins, soils, urban regions, and phytoplankton zones.

Edges represent carbon flux, heat transfer, trade influence, and policy interactions.

This structure enables the system to learn how changes in one region propagate globally.

Graph Neural Networks in Practice

Graph Neural Networks (GNNs) are implemented using PyTorch Geometric. A simplified conceptual example is shown below:

```
from torch_geometric.nn import GCNConv

class EarthGNN(torch.nn.Module):
    def __init__(self):
        super().__init__() self.conv1 = GCNConv(3,
        16) self.conv2 = GCNConv(16, 1)

    def forward(self, x, edge_index): x = self.conv1(x,
        edge_index).relu() return self.conv2(x, edge_index)
```

This model learns how carbon states evolve across interconnected regions.

Physics-Informed Ocean and Biosphere Modeling

Carbon absorption follows physical and biological laws. To ensure scientific validity, CARBONOSPHERE-AI uses Physics-Informed Neural Networks (PINNs).

These models embed constraints such as:

- Ocean carbon saturation limits
- Temperature-driven solubility
- Phytoplankton growth dynamics

This prevents unrealistic predictions and improves interpretability.

Neuromorphic Memory for Long-Term Dynamics

Carbon sinks exhibit delayed responses and sudden tipping points. To model this behavior, the system employs neuromorphic memory inspired by biological neurons.

Spiking Neural Networks act as the long-term memory of the planet, allowing the system to:

- Learn decade-scale trends

Detect early warning signs of collapse

- Anticipate irreversible transitions

This converts climate modeling from reactive forecasting to anticipatory intelligence.

Carbon Sink Optimization Using Reinforcement Learning

CARBONOSPHERE-AI does not merely observe the planet; it actively designs strategies.

Using Proximal Policy Optimization (PPO), the system learns where and how to:

- Restore forests and wetlands

- Deploy algae-based ocean sinks
- Balance sequestration with biodiversity and land use

A simplified policy interaction is illustrated below:

```
action = policy(state)
next_state, reward =
environment.step(actio
n) policy.update(state,
action, reward)
```

Economic and Policy Digital Twin

Environmental solutions must be feasible. CARBONOSPHERE-AI includes an economic and policy simulation layer that models:

- Carbon credit markets
- Government incentives
- Corporate compliance and manipulation risks

Agent-based modeling ensures that proposed strategies survive real-world constraints.

Interactive Visualization and Digital Twin Interface

The system includes an interactive dashboard built using Plotly Dash, providing:

- 3D planetary visualization
- Live carbon flux coloring

  Greenhouse gas composition charts
- PPO training evolution plots

These visualizations transform complex data into intuitive insight.

Environmental Impact

By focusing on carbon sinks, CARBONOSPHERE-AI contributes to:

- Long-term climate stabilization
- Ecosystem restoration
- Evidence-based environmental policy
- Risk-aware climate planning

Future Development

Future extensions include:

- Higher-resolution regional twins
- Biodiversity and water-cycle integration
- Real-time satellite data assimilation
- Global climate negotiation simulators

The architecture is designed to evolve continuously.

Conclusion

CARBONOSPHERE-AI redefines climate intelligence by treating carbon regulation as a cognitive, adaptive, and systemic challenge. By integrating physical laws, artificial intelligence, economic reasoning, and interactive visualization, the system offers a powerful framework for understanding and governing Earth’s carbon future.

Rather than predicting collapse, CARBONOSPHERE-AI is designed to help prevent it.

CARBONOSPHERE-AI: A Planetary Digital Twin for Carbon Sink Intelligence and Climate Regulation

Explained as a Conversation Between Researchers

Aniket Agarwal
Bachelor of Technology, Computer Sciences Amity University, Punjab, India

Conversation Between Two Researchers

Researcher 1 (R1): I am excited to share our new project, CARBONOSPHERE-AI, which is a self-evolving digital twin of the Earth focused on carbon sinks and greenhouse gas regulation.

Researcher 2 (R2): Interesting! But first, why do we need such a project? Aren't current climate models sufficient?

R1: Good question. Current climate models mainly focus on emissions reduction and predicting temperature changes. But carbon sinks—the forests, oceans, and soils that absorb CO_2—are not dynamically optimized. They are complex, slow-responding, and prone to sudden tipping points. CARBONOSPHERE-AI fills this gap by actively modeling and governing these sinks.

R2: So, you are saying it focuses on carbon absorption rather than just emissions? How does that help the environment?

R1: Exactly. By understanding and managing carbon sinks, we can stabilize the carbon cycle. This prevents excess CO_2 from accumulating, reduces climate risk, and promotes ecosystem restoration. Essentially, it targets the root cause of atmospheric carbon imbalance rather than just its source.

R2: I see. Can you explain the core idea of the project in simple terms?

R1: Think of Earth as a living network where regions like forests, oceans, and soils interact. Each region is a node in a graph, and the interactions—like carbon flux—are edges. We then simulate how interventions in one area affect others globally. We use Graph Neural Networks (GNNs) to learn these interactions.

R2: How does a Graph Neural Network help here?

R1: GNNs capture complex spatial dependencies. For example, cutting a forest in one region might increase carbon in the atmosphere, which impacts oceanic absorption elsewhere. GNNs learn these patterns automatically. Here's a minimal example:

```
from torch_geometric.nn import GCNConv

class EarthGNN(torch.nn.Module):
    def __init__(self):
        super().__init__() self.conv1 = GCNConv(3,
        16) self.conv2 = GCNConv(16, 1)

    def forward(self, x, edge_index): x = self.conv1(x
        edge_index).relu() return self.conv2(x, edge_index)
```

R2: That's clear. But carbon sinks follow physical laws. How do you make sure the AI predictions are realistic?

R1: Great point. We use Physics-Informed Neural Networks (PINNs) to embed constraints like ocean solubility limits and phytoplankton growth dynamics. This ensures that the AI never predicts physically impossible outcomes.

R2: Interesting. What about long-term trends and delayed effects?

R1: Carbon sinks respond slowly. To capture this, we integrate neuromorphic memory using spiking neural networks. These networks remember decade-scale patterns and detect early warning signs of tipping points.

R2: And you mentioned it actively controls carbon sinks. How does that work?

R1: We use reinforcement learning, specifically Proximal Policy Optimization (PPO). The AI experiments with interventions like reforesting or enhancing oceanic sinks, observes their impact, and updates its strategy to maximize carbon absorption.

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```
action = policy(state)
next_state, reward =
environment.step(actio
n) policy.update(state,
action, reward)
```

R2: What about software and implementation? How is this actually running?
R1: We use a mix of Python libraries:

- **PyTorch + PyTorch Geometric** for GNNs and learning spatial interactions.
- **PINNs** implemented in TensorFlow or PyTorch for physics constraints.
- **Gym + PPO** for reinforcement learning of intervention policies.
- **Plotly Dash** for interactive 3D visualization of carbon flux and sink states.
- **NetCDF + ERA5 data** for real-world ocean and atmospheric inputs.

R2: Can you show an example of how visualization works?
R1: Sure. We create interactive 3D graphs where node color indicates carbon flux:

```
import plotly.graph_objects as go

fig = go.Figure(data=[go.Scatter3d( x=positions_x, y=positions_y, z=positions_z, mode='markers',
      marker=dict(size=5, color=carbon_flux, colorscale='Viridis')
)]) fig.show()
```

R2: Wow, that's interactive and intuitive. How does this project differ from other carbon models?

R1: Most models are static, predictive, and isolated. CARBONOSPHERE-AI is adaptive, integrates AI with physics, economics, and policy, and interacts with the system dynamically. It can propose optimal interventions instead of just predicting scenarios.

R2: Could this help in real-world climate policy?

R1: Absolutely. Policymakers could use our simulations to test interventions, prioritize areas for restoration, and assess trade-offs between economic cost and environmental benefit.

R2: How can this project be further developed in the future?
R1: Future directions include:

- Higher-resolution regional twins
- Integration of biodiversity and water cycles
- Real-time satellite data assimilation
- Global climate negotiation and policy simulations

R2: And overall, how will it impact the environment?

R1: By focusing on carbon sinks, it stabilizes atmospheric CO_2, restores ecosystems, informs better climate strategies, and helps prevent catastrophic tipping points.

R2: That's revolutionary. Finally, what is the main takeaway?

R1: CARBONOSPHERE-AI transforms climate modeling from static prediction to adaptive, proactive, sink-centric intelligence. It bridges science, policy, and technology to actively safeguard the planet's carbon balance.

R2: I'm convinced. This is indeed a paradigm shift in climate intelligence.