

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

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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 (CO₂, CH₄, N₂O) 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 CO₂, CH₄, and N₂O 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:** CO₂, CH₄, N₂O 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)

```

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 decision-makers with actionable insights for climate mitigation.

VII. ENVIRONMENTAL IMPACT

By actively managing carbon sinks:

- Atmospheric CO₂ 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

- [1] Rolnick, D., et al., “Tackling Climate Change with Machine Learning,” *arXiv preprint arXiv:1906.05433*, 2019.
- [2] Reichstein, M., et al., “Deep Learning and Process Understanding for Data-Driven Earth System Science,” *Nature*, 566: 195–204, 2019.
- [3] Tao, F., et al., “Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications and Research Issues,” *Robot. Comput. Integr. Manuf.*, 2018.
- [4] Wu, Z., et al., “A Comprehensive Survey on Graph Neural Networks,” *IEEE Trans. Neural Netw. Learn. Syst.*, 32(1): 4–24, 2021.
- [5] Schulman, J., et al., “Proximal Policy Optimization Algorithms,” *arXiv:1707.06347*, 2017.