

Aero-Twin Ulaanbaatar: Physics-Informed Neural Networks and IoT-Enabled Ground Validation for Micro-Climate Air Quality Downscaling

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Abstract

Atmospheric particulate matter PM2.5 dynamics within the Ulaanbaatar basin present a severe modeling challenge due to intense winter-time deep thermal boundary layer inversions. Standard empirical models fail to encapsulate fine-grained spatial configurations dictated by topographies. To resolve this, this research implements a Physics-Informed Neural Network (PINN) framework that embeds fluid mechanics constraints directly into deep learning layers, achieving continuous downscaled air quality maps.

Introduction

During winter in Ulaanbaatar, high-density cold air masses become trapped beneath stagnant warm layers within the valley canopy, preventing traditional advective clearance. This locks emissions from domestic heating (ger districts) into concentrated urban micro-zones, creating sharp sub-kilometer pollution gradients. Traditional machine learning models often yield unphysical predictions in areas with sparse monitoring stations. By encoding fluid mechanics equations into the neural network, we constrain spatial modeling to strictly comply with real-world physical boundaries.

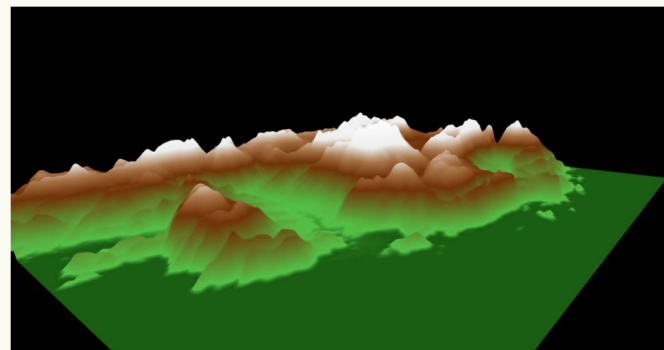
Methods and Materials

The spatiotemporal evolution of the dense aerosol dispersion field is mathematically constrained by the classic Eulerian Advection-Diffusion partial differential equation:

$$\frac{\partial C}{\partial t} + v \frac{\partial C}{\partial x} + \nabla^2 C = R - (\lambda + s + d)C$$

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To acquire ground-truth measurements, an IoT edge-computing sensor array (Plantower PMS5003 counters connected to ESP8266 microcontrollers) was deployed across micro-climatic zones. High-resolution Digital Elevation Model (DEM) grids 1200m to 2400m enforce slip conditions directly at the terrain-fluid interfaces



Main process:

Deploying IoT edge nodes equipped with PMS5003 laser counters across 9 municipal stations to stream continuous validation dataset.

IoT Sensor Array

Terrain DEM Constraints

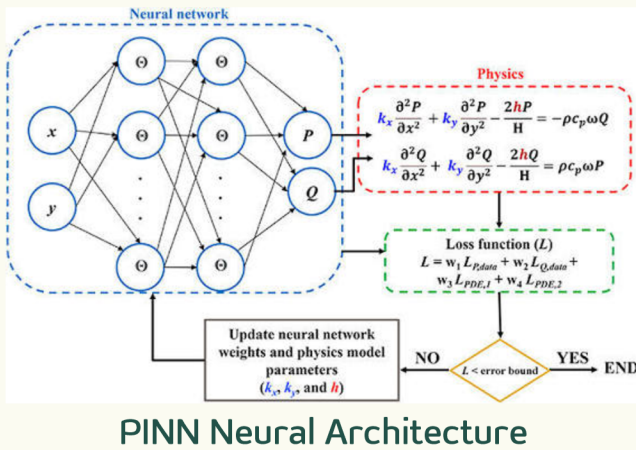
PINN

High-Fidelity Training

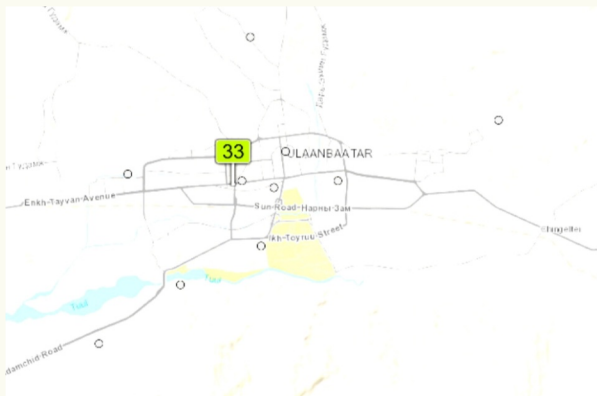
Micro-Scale Downscaling



IoT Edge Sensor Node Array



PINN Neural Architecture



Downscaled Micro-Climate Map

Result & Metrics

No. of the station	AQ monitoring site	Latitude	longitude	Station location
1	Zuun ail (UB5)	47.932881	106.921331	Residential apartment area
2	Selbe 5 buudal (UB12)	47.954043	106.920997	Residential ger area, 450 m from the highway
3	Hailaast (UB11)	47.958191	106.901784	Residential ger area, 100 m from the highway
4	Dambadarjaa (APRD5)	47.962993	106.932177	10 m away from the highway and 1.2 km to the southwest is the Selbe power station
5	Zuun 4 zam (UB4)	47.917495	106.937537	City center
6	Bogdkhaanii museum (UB13)	47.897106	106.906859	Residential apartment area, 100 m from the highway
7	Nisekh (APRD4)	47.863938	106.779077	Residential ger area
8	Tolgoit (APRD1)	47.9224455	106.794781	Residential ger area, 230 m from the highway
9	Bayankhoshuu (APRD6)	47.957603	106.822841	Residential ger area
10	MNB (APRD2)	47.929720	106.888636	Residential apartment area
11	Baruun 4 zam (UB2)	47.915392	106.894185	City center
12	1-r horoolol (UB3)	47.917940	106.848160	Residential ger area
13	Amgalan (APRD3)	47.913433	106.997969	Residential apartment area, 600 m away from the

Discussion

Traditional machine learning models suffer from fluid boundary leakage, erroneously predicting air pollution transport through mountain ranges. By enforcing physics constraints directly into neural network loss layers, the Aero-Twin framework naturally directs dense particulate matter to accumulate and stagnate within low-lying urban valleys, matching the intense pollution gradients captured empirically by our physical IoT stations.

Conclusion

Embedding fluid dynamics conservation laws into deep learning layers provides a robust alternative to capital-intensive air monitoring infrastructure. This highly scalable, physics-bounded architecture yields high-fidelity block-level predictions across enclosed complex terrains, offering actionable real-time spatial analytics for environmental risk management and urban public health policy design.

References

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- National Center for Public Health. Air Quality Telemetry Data Array Updates for Ulaanbaatar Basin Station Pipelines (2025-2026).
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