Hourly $PM_{2.5}$ Mapping over Africa using Cross-Sensor Calibration and Advanced Transfer Learning

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OVERVIEW

Objective: Our goal is to produce operational $PM_{2.5}$ product over Africa using geostationary satellite observations.
Challenge: Africa has limited $PM_{2.5}$ monitoring stations versus 1000+ stations in US, limiting air quality assessment over the continent.
Approach: We develop a transfer learning framework adapting a deep neural network trained on GOES-ABI (CONUS) to MTG-FCI (Africa) via cross-sensor calibration.

1. $PM_{2.5}$ ESTIMATION OVER CONUS

1.1 Data & Coverage

- **Target:** 1,236 AirNow $PM_{2.5}$ monitors; full-year 2023 daylight retrievals
- **Processing:** Hourly CONUS grid (±30 min aggregation); GOES-E/W merged at ~106°W; cloud masking applied
- **Product:** Continuous $PM_{2.5}$ fields beyond point monitors

1.2 Model Architecture & Training

- **Inputs:** ABI reflectance (C01-C04), HRRR meteorology, satellite geometry (SZA/VZA/RAA)
- **Architecture:** 3-layer DNN (128→256→16) with ReLU, BatchNorm, Dropout (0.1)
- **Training:** 80/10/10 train/val/test split; Adam optimizer (lr=0.005), MSE loss

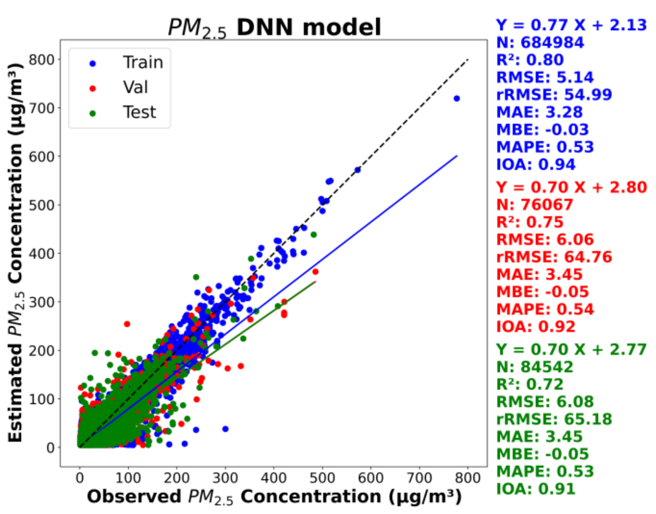


Figure: Scatter plot of observed AirNow $PM_{2.5}$ vs DNN-estimated $PM_{2.5}$ for 2023. Random split of 90/10/10 (train/validation/test) dataset (Park et al., 2025)

1.3 Validation Results

- **Random 10-fold CV :** IOA = 0.91, RMSE = 6.14 µg/m^3, rRMSE = 66.34%.
- **Spatial 10-fold CV:** IOA = 0.89, RMSE = 6.61 µg/m^3, rRMSE = 72.14%.
- **Temporal 10-fold CV :** IOA = 0.85, RMSE = 8.50 µg/m^3, rRMSE = 89.68%.

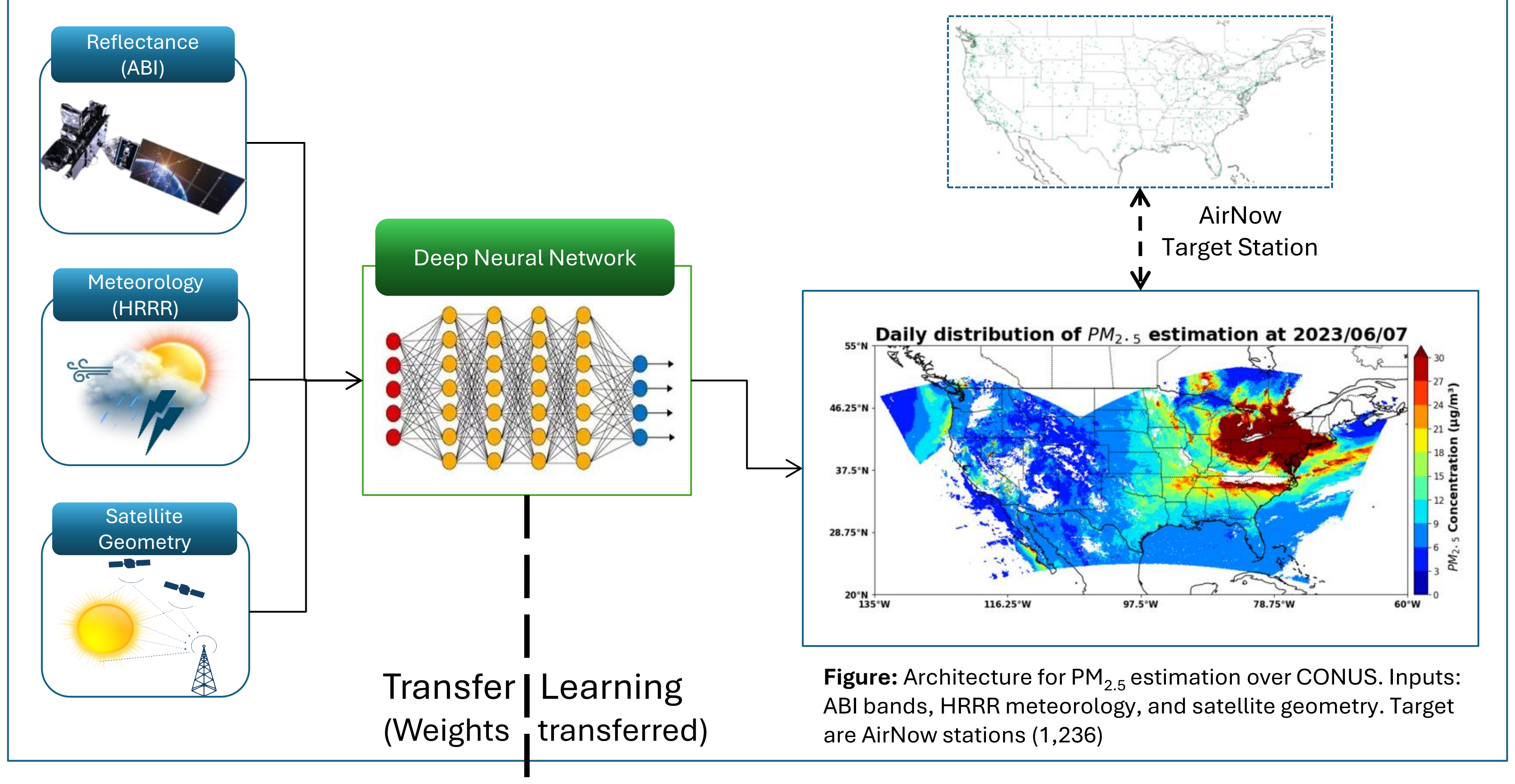


Figure: Architecture for $PM_{2.5}$ estimation over CONUS. Inputs: ABI bands, HRRR meteorology, and satellite geometry. Target are AirNow stations (1,236)

2. CROSS SENSOR CALIBRATION

2.1 Objective: Characterize systematic reflectance differences between ABI and FCI due to varying instrument characteristics and viewing geometries to enable accurate cross-sensor calibration for model transfer.

2.2 Collocation Methodology

- **Spatial matching:** ABI-FCI pairs via KD-tree nearest neighbor (≤5 km threshold)
- **Test case:** Cloud-free coincident scene over Brazil, 2025-01-29, 14:10 UTC.

Table: ABI–FCI band pairs over Brazil, 2025-01-29 14:10 UTC (cloud-free). Shows native to target resolution, correlation *R* between reflectance factors, and correlations of ΔRF with VZA.

Bands paired	Resolutions (ABI / FCI → target)	*R* (RF)	R_{vz} (ΔRF; FCI VZA)	R_{vz} (ΔRF; ABI VZA)
C01 – VIS_04 (0.470 vs 0.444 µm)	1 km / 1 km → 1 km	0.173	+0.678	−0.687
C02 – VIS_06 (0.640 vs 0.640 µm)	0.5 km / 1 km → 1 km	0.506	+0.212	−0.239
C03 – VIS_08 (0.865 vs 0.865 µm)	1 km / 1 km → 1 km	0.724	+0.339	−0.325
C04 – NIR_13 (1.370 vs 1.380 µm)	2 km / 1 km → 2 km	0.473	+0.213	−0.195

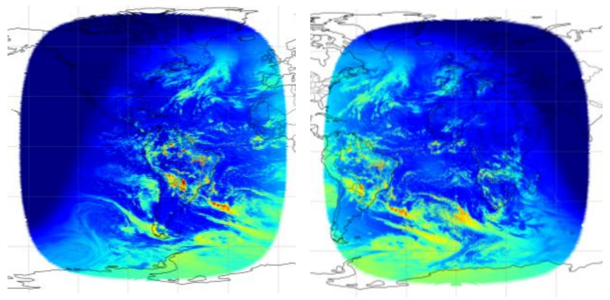
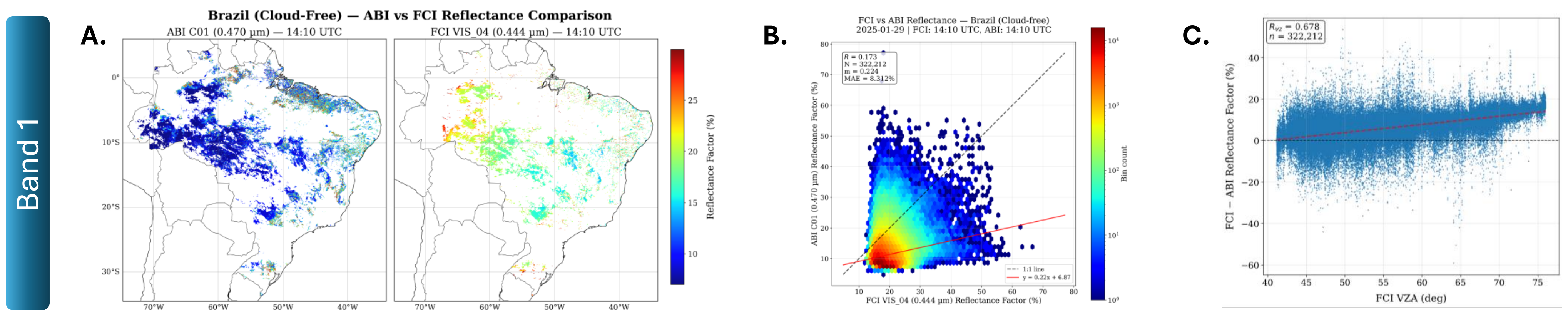


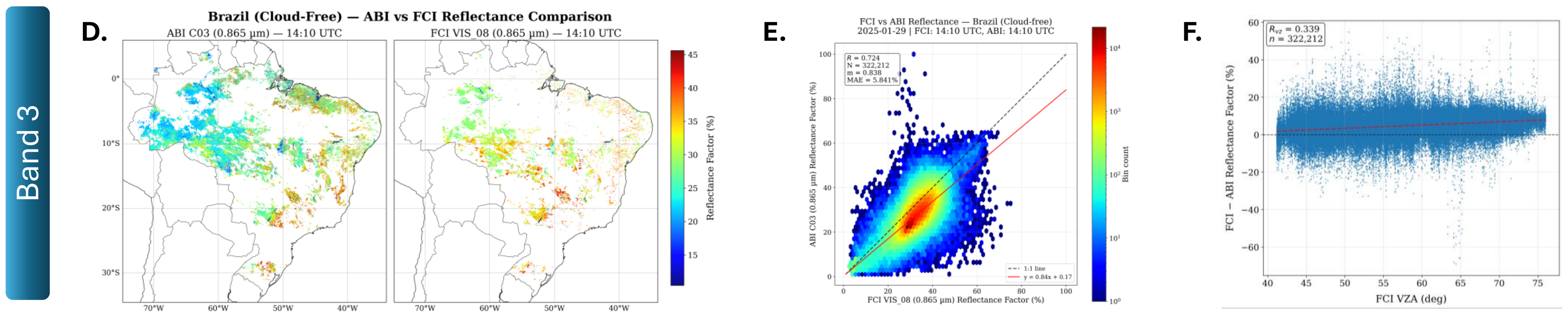
Figure: Full-disk reflectance from GOES-16 ABI C01 (0.47 µm) and MTG-I FCI VIS_04 (0.444 µm) on January 29, 2025, 14:10 UTC.

2.3 Viewing Geometry Effects

- **VZA-induced error:** As FCI VZA increases and ABI remains nadir, pixel mismatch widens and ΔRF grows (*R*=+0.678 vs FCI VZA; *R*=−0.687 vs ABI VZA in Band 1)
- **Wavelength dependency:** Rayleigh scattering ($\sim\lambda^{-4}$) amplifies geometry effects at short wavelengths. Band 1 (0.47 µm) shows strongest VZA sensitivity and lowest ABI-FCI agreement (*R*=0.17); Band 3 (0.865 µm) has weaker VZA sensitivity (*R*=0.339) and higher agreement (*R*=0.724)
- **Implication:** Band-specific linear calibration required for transfer learning.



Figures A-C: ABI C01 vs FCI VIS_04 reflectance maps, hexbin scatter, and ΔRF vs VZA relationship



Figures D-F: ABI C03 vs FCI VIS_08 reflectance maps, hexbin scatter, and ΔRF vs VZA relationship

3. $PM_{2.5}$ ESTIMATION OVER AFRICA (Ongoing Work)

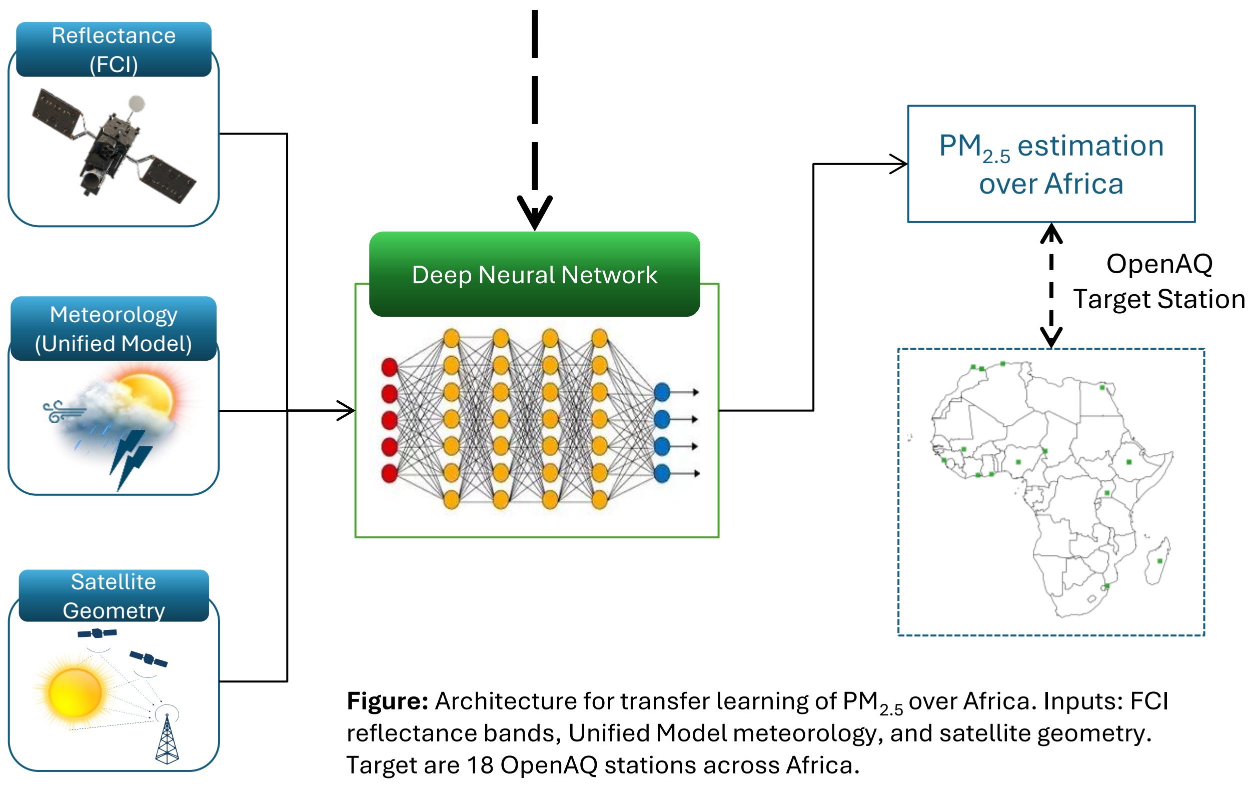


Figure: Architecture for transfer learning of $PM_{2.5}$ over Africa. Inputs: FCI reflectance bands, Unified Model meteorology, and satellite geometry. Target are 18 OpenAQ stations across Africa.

3.1 Transfer Learning Approach

- **Rationale:** Leverages knowledge from data-rich CONUS to overcome data scarcity in Africa. FCI L2 data is only available since January 2025.
- **Mechanism:** Pre-trained model captures fundamental aerosol-radiation relationships (smoke signatures, scattering patterns) transferable across regions, requiring only fine-tuning for African-specific conditions (dust vs. biomass burning) rather than training from scratch
- **Advantage:** Circumvents need for extensive ground-truth data by initializing with CONUS-learned $PM_{2.5}$-reflectance relationships

3.2 Domain Adaptation Strategy

- **Sensor mapping:** FCI bands → ABI bands using band-specific linear calibration from Section 2
- **Meteorology mapping:** Unified Model (UM) → HRRR with standardization; include geometry (SZA/VZA/RAA)
- **Architecture:** Add adapter layer if feature mismatch persists; fine-tune with early layers frozen

3.3 Fine-Tuning Protocol

- **Stage 1:** Train adapter and output layer with CONUS DNN early layers frozen
- **Stage 2:** Unfreeze last hidden layer; fine-tune with reduced learning rate

3.4 Expected Outcomes

- Hourly $PM_{2.5}$ at 2-km resolution over Africa; spatial validation at OpenAQ stations

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Reference: Park, S., Sayeed, A., Seo, J., Henderson, B. H., Naeger, A. R., & Gupta, P. (2025). Hour by hour PM2.5 mapping using geostationary satellites. ACS ES&T Air, 2(9), 1816–1830. doi.org/10.1021/acsestair.4c00365