AQpicture Workshop
24/11/2025

Air Quality from pictures: Benchmarking and assessment of image-based methods for particulate matter estimation

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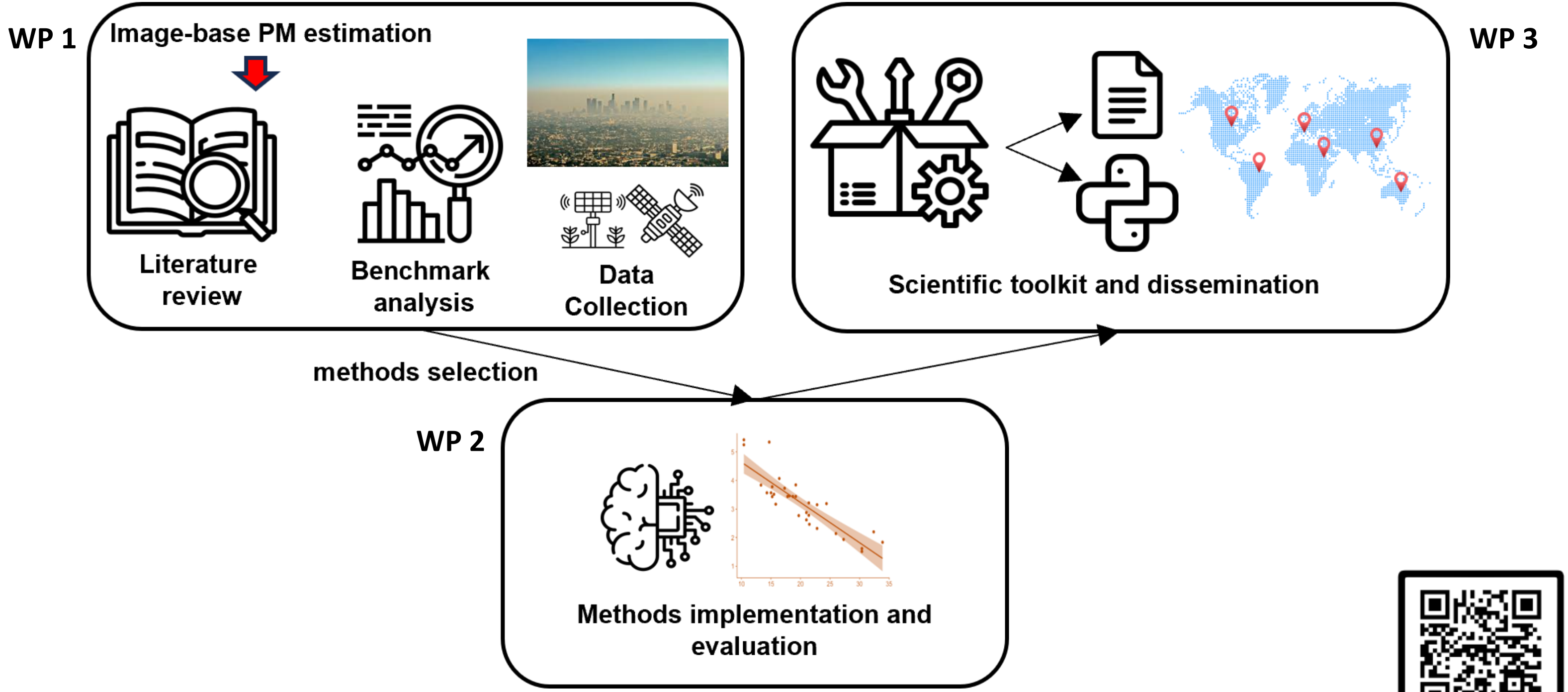
The ISPRS Scientific Initiative is a collaborative research effort launched by the International Society for Photogrammetry and Remote Sensing (ISPRS) to promote innovative, interdisciplinary projects that advance the development and application of photogrammetry, remote sensing, and spatial information sciences for global scientific and societal benefits.

The **AQPicture** project is funded by **ISPRS Scientific Initiative 2025** and aims to:

- Evaluate the accuracy and applicability of existing image-based PM estimation methods by implementing and testing them against authoritative ground sensor measurements and satellite aerosol products.
- Develop a scientific toolkit that includes open-source code scripts, analysis-ready datasets, and technical documentation to support replication and adaptation of these methods by other researchers and practitioners.
- Promote the use of image-based air quality monitoring by making the toolkit freely available and organizing dissemination activities, such as workshops and scientific publications, to share results and encourage further research and application in the field.

https://www.isprs.org/society/si

AQPicture

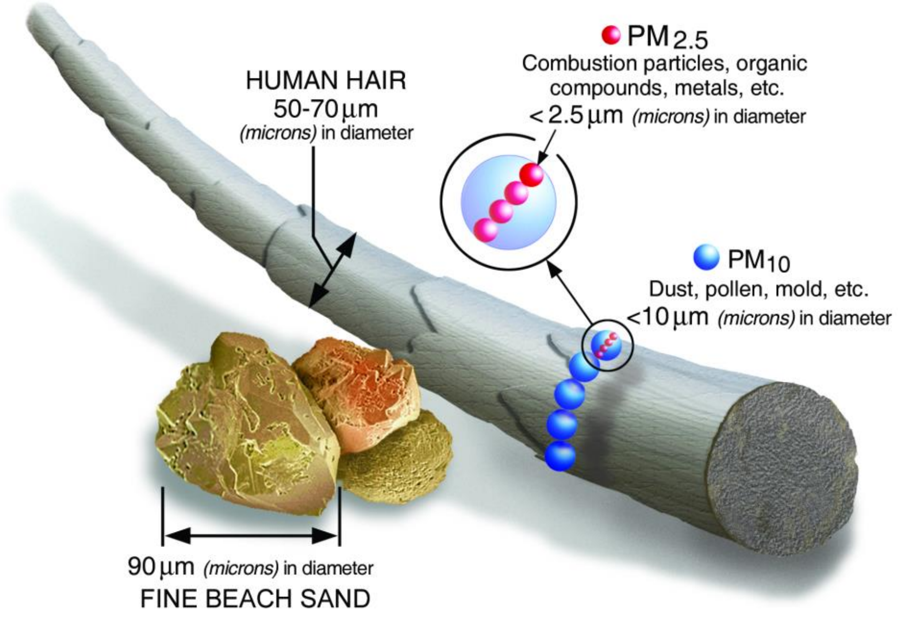


- Github repository: https://github.com/gisgeolab/aqpicture.git (Under Construction)

Scan me!

Introduction

- Particulate matter (PM) is a mixture of solid and liquid particles such as dust, pollen, ash, soot, dirt, and smoke, some visible as haze and others too small to see with the naked eye.



Source: United States Environmental Protection Agency

PM is categorized by particle size

- Particles 10 micrometers or larger
- Particles 10 micrometers or smaller (PM10)
- Particles 2.5 micrometers or smaller (PM2.5)
- Particles under 1 micrometer (PM1)

- Both PM10 and PM2.5 are inhalable particles, meaning they can be breathed deep into the lungs, posing health risks.
- PM1 particles are the smallest and potentially more harmful due to their ability to penetrate deeper into the respiratory system, but they are less commonly monitored or regulated compared to PM2.5 and PM10.
- Inhalation of PM2.5 can lead to aggravated asthma, bronchitis, reduced lung function, and increased risk of heart attacks and strokes.
- Long-term exposure is associated with chronic respiratory diseases, cardiovascular problems, and premature death.
- Vulnerable populations, such as children, the elderly, and those with pre-existing health conditions, are at higher risk.

Introduction

Source: ubreath

- PM2.5 originates from a mixture of natural and human-made sources, with human activities being the dominant contributors in urban areas.
- Major anthropogenic sources include vehicle exhaust emissions, industrial processes, residential heating (biomass and fossil fuel combustion), and power plants.
- Secondary inorganic aerosols formed from atmospheric chemical reactions of gases such as sulfur dioxide (SO2), nitrogen oxides (NOx), and ammonia (NH3) also contribute significantly to PM2.5 mass.
- Natural sources include soil and road dust resuspension, sea salt, and biogenic emissions, although these are generally less impactful in highly urbanized environments.

Introduction

- **<u>Gravimetric sampling</u>**: Air is drawn through filters that collect PM2.5, and filters are weighed to measure particle mass.
- **<u>Beta attenuation monitors (BAM)</u>**: Measure PM2.5 mass via the attenuation of beta radiation through particles.
- **<u>Tapered element oscillating microbalance (TEOM)</u>**: Measures particle mass by detecting frequency changes in a vibrating filter element.
- **<u>Light scattering sensors/photometers</u>**: Provide real-time PM2.5 concentration based on light scattered by airborne particles.
- These methods vary in cost, complexity, and accuracy; gravimetric and BAM are standard for regulatory monitoring, while light-scattering is increasingly used for real-time applications.

Introduction

- Gravimetric methods are accurate but labor-intensive, requiring filter collection, lab analysis, and time delays, limiting real-time data availability.
- Beta attenuation monitors and TEOM are costly, bulky, and require regular maintenance, making widespread dense monitoring difficult.
- Light-scattering sensors provide real-time data but can be less accurate and sensitive to environmental factors like humidity and particle composition.
- Conventional methods often lack spatial resolution due to limited number of fixed monitoring stations, missing local pollution variability and exposure hotspots.
- High costs and operational complexity restrict deployment in resource-limited or large-area monitoring scenarios.

✓ **AQPicture offers potentially low-cost, near real-time monitoring with higher spatial resolution by using advanced image processing and machine learning to estimate PM2.5 from outdoor CCTV or camera images.**

Literature Reveiw

Framework: PRISMA.

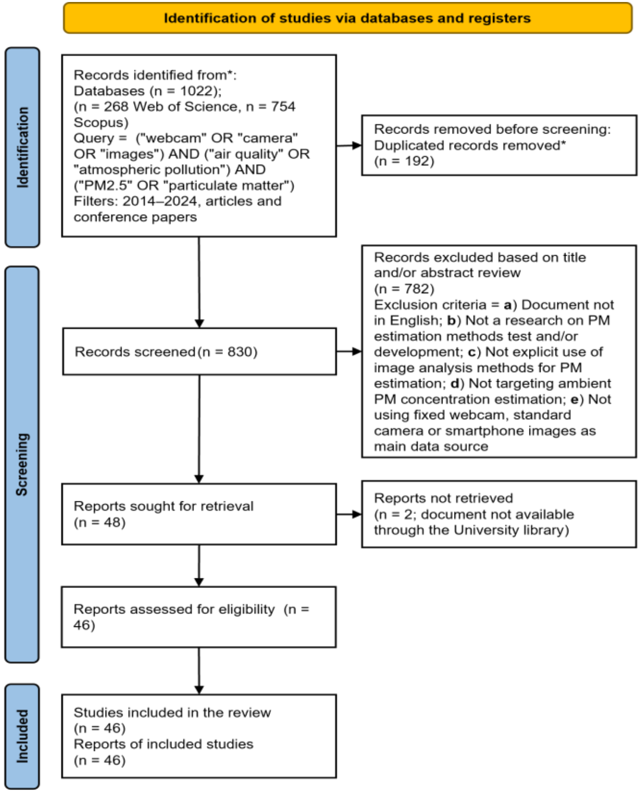
Bibliographic Databases:
- Web of Science
- Scopus

Targets:
- Peer-reviewed journal articles
- Conference Proceedings

Timeframe: 2014 to 2024.

Imaging-related keywords:
- Image-based
- Photograph
- Camera
- Visibility
- Haze detection

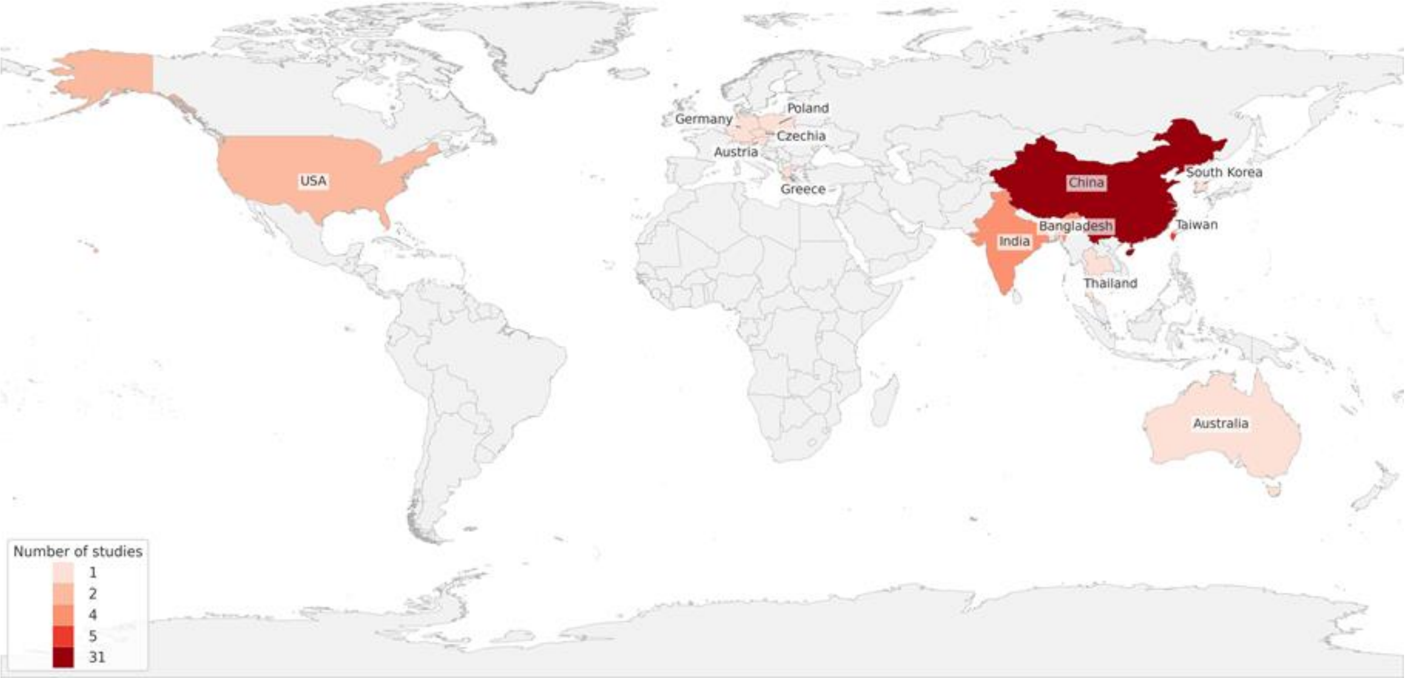
Pollutant-specific keywords:
- PM2.5
- Particulate matter
- Air quality



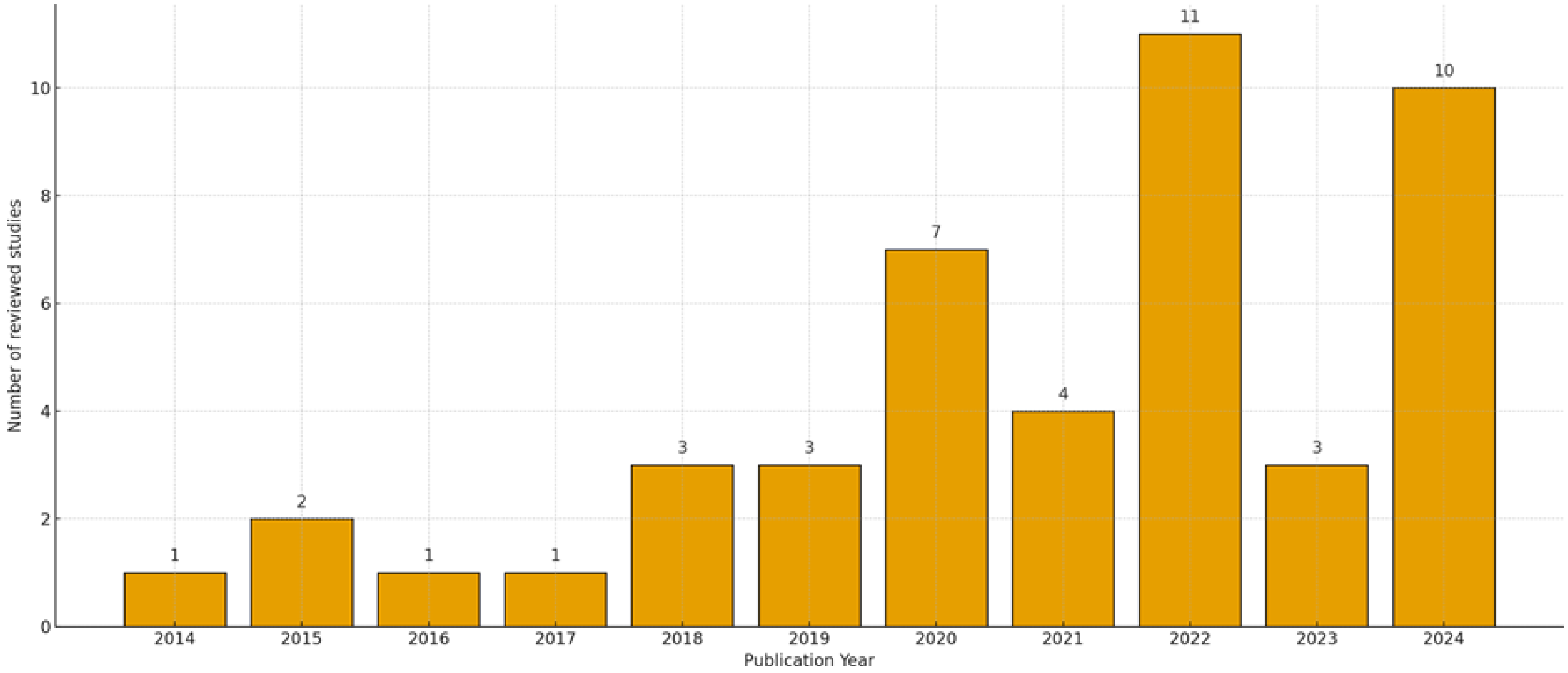
*AI used to parse record lists and remove duplicates

Literature Reveiw

- Geographic distribution is not necessarily linked to author nationalities or to author institutional affiliations.
- Multi-country studies are counted once for each country involved.



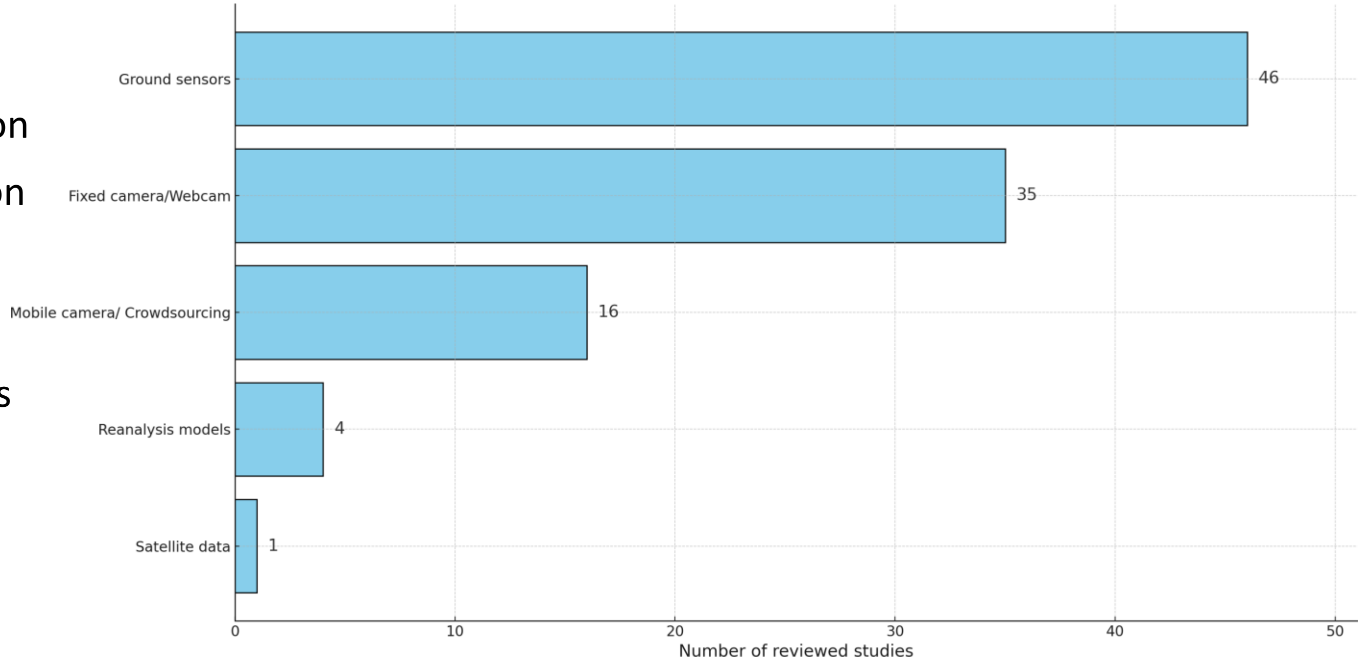
- Year distribution of the selected studies.



- Image-based PM estimation uses diverse data sources.

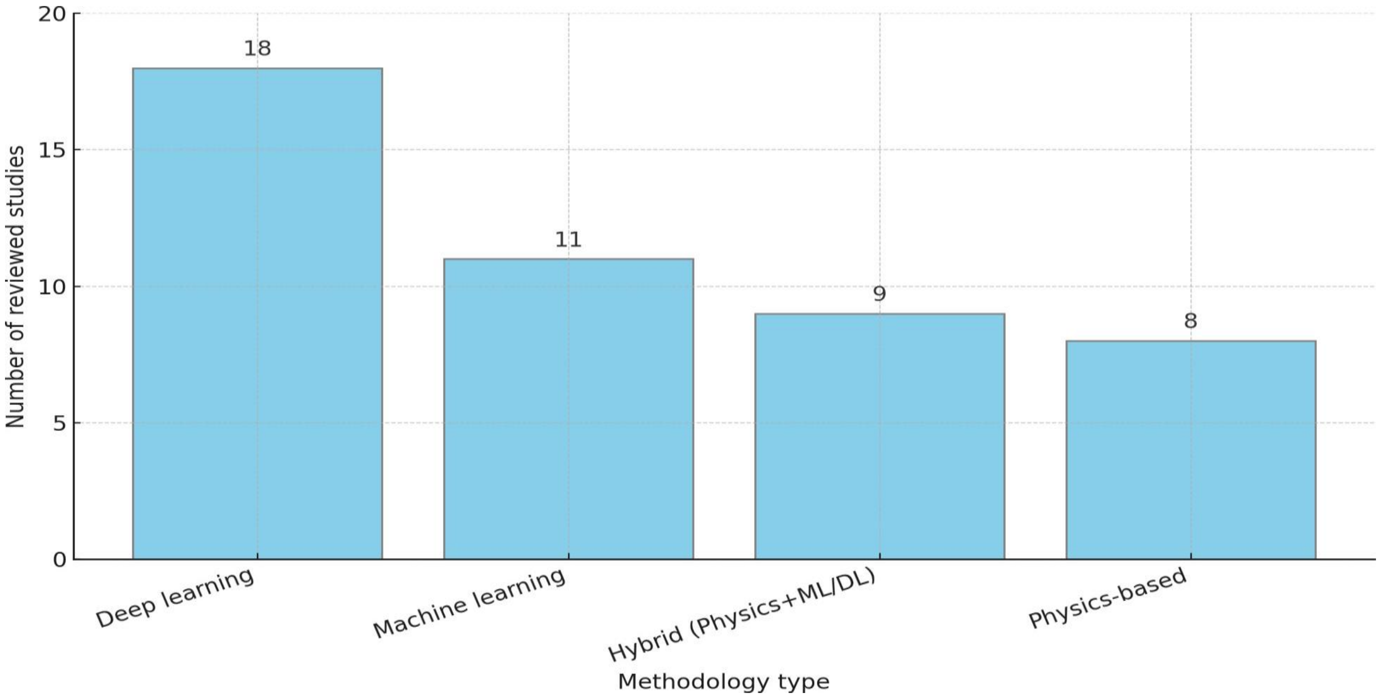
Typical pre-processing steps include:

- Radiometric calibration
- Histogram equalization
- Sky segmentation
- Dehazing
- Geometric corrections

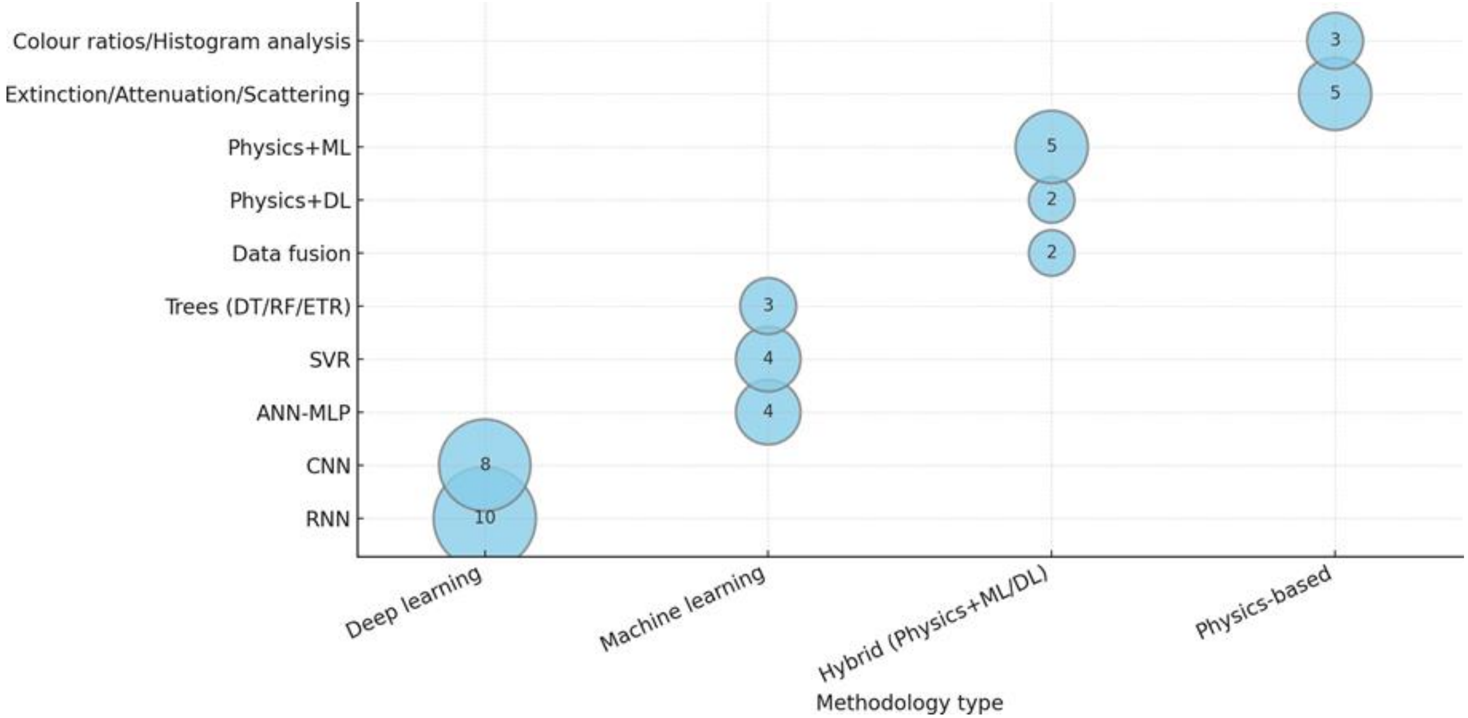


Literature Reveiw

- Methodologies are grouped into 4 types: Physics-based, Machine Learning (ML), Deep Learning (DL), and Hybrid.

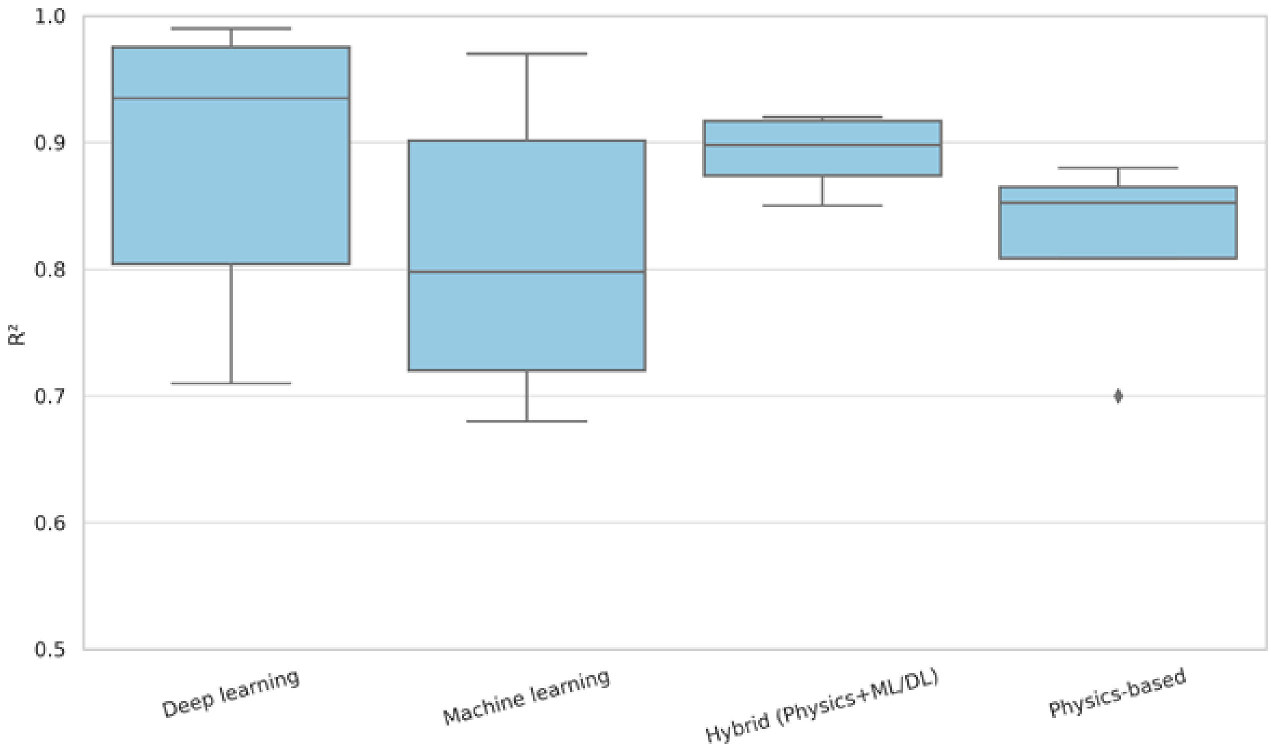


- Distribution of methodology sub-types:



Literature Reveiw

- **RMSE** is dependent on absolute PM concentration levels, making cross-study comparison difficult.
- R^2 is used as the preferred reference metric for qualitative comparison because it is independent of absolute concentration levels and measures the proportion of variance explained by models.
- Most methods DON'T meet generic regulatory requirements ($R^2 > 0.90$*).



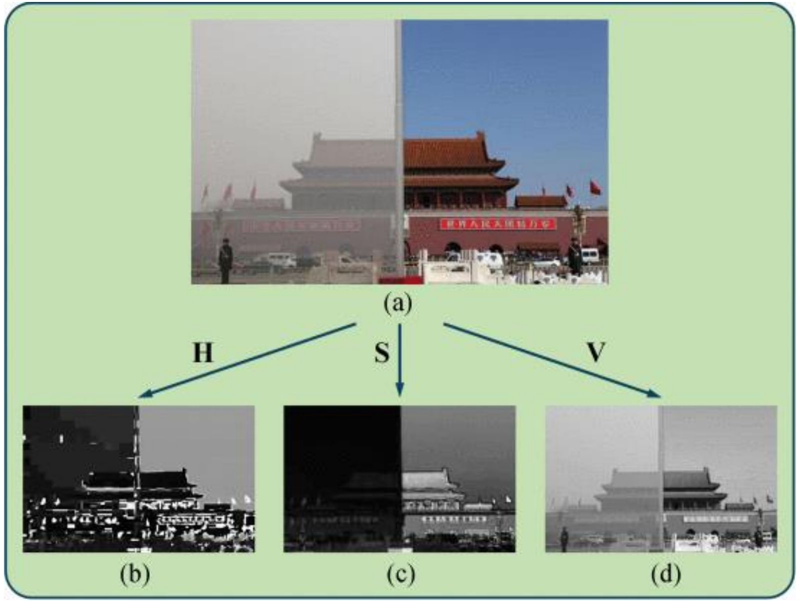
*Watson et al. (1998). *Guidance for using continuous monitors in PM2.5 monitoring networks.*

Literature Reveiw

Challenge	Why It Matters	Research Direction
Limited multi-site datasets	Models don't transfer across regions/seasons	Collect larger, more diverse datasets
Atmospheric/lighting variability	Performance drops in clouds, fog, rain	Robust preprocessing (dehazing, calibration)
Reproducibility	Hard to benchmark models systematically	Mandate open code + standardized metrics
Regulatory gap	Can't replace ground monitoring yet	Physics-informed DL models + auxiliary meteorological data

Physics-Based Model

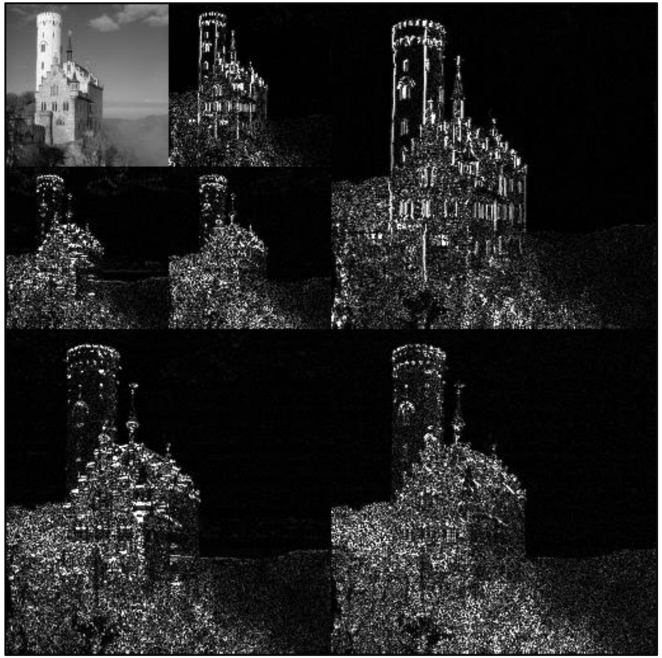
- **Paper DOI:** [10.1109/TIE.2018.2840515](https://doi.org/10.1109/TIE.2018.2840515)



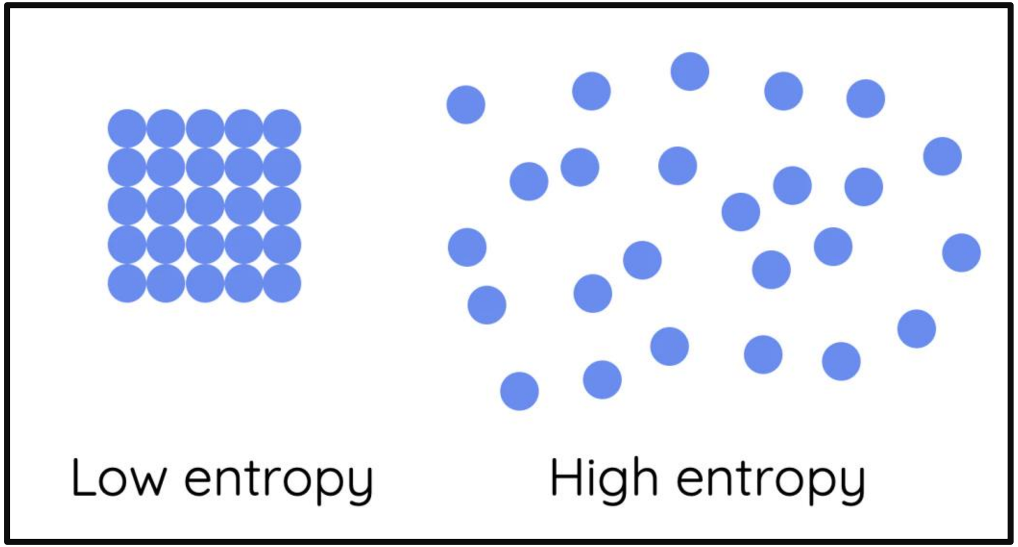
Images are first converted to HSV colour space and then the Saturation map is extracted.

- Naturalness of a picture decreases as the concentration of PM2.5 increases.
- This degradation is primarily reflected in the image's **contrast** and **saturation**.
- Higher pollution levels reduce visibility and make images appear more colourless and hazy.
- As PM2.5 levels rise, the saturation of pixels in an image tends to drop, causing the overall saturation map to become more **stable and orderly**.

Feature Extraction



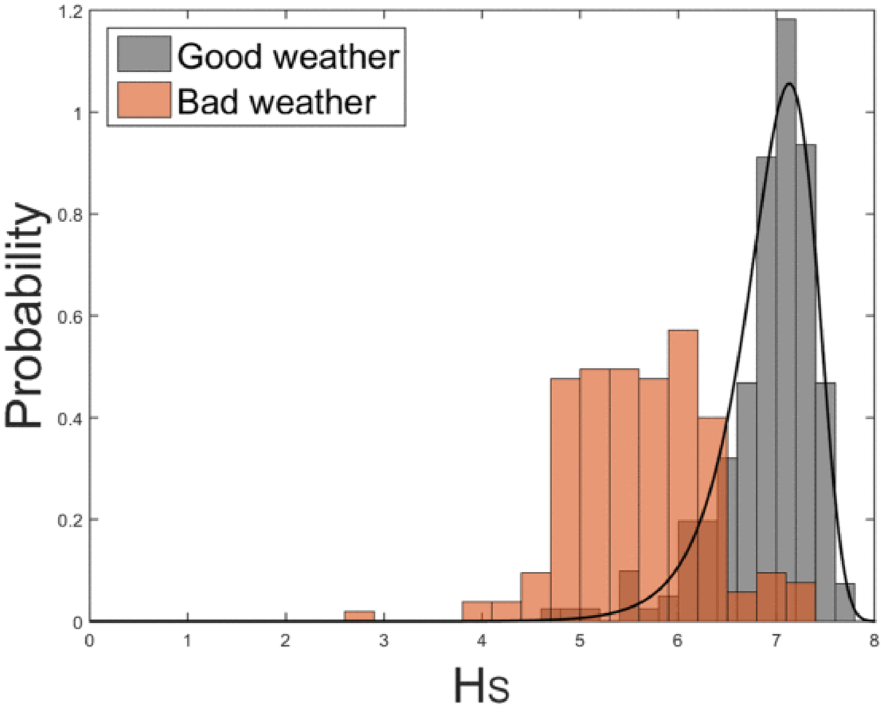
Haar Wavelet Transform



Concept of Entropy

Feature A: Spatial Domain Entropy (HS)

- Step: Calculate the entropy of the saturation map directly.
- Reason: In clear weather (low PM2.5), images have high contrast and rich colour variation (high entropy). In polluted weather, the saturation map becomes uniform and grey (low entropy).
- Observation: The distribution of these entropy values for clear-weather images follows an Extreme Value Distribution.

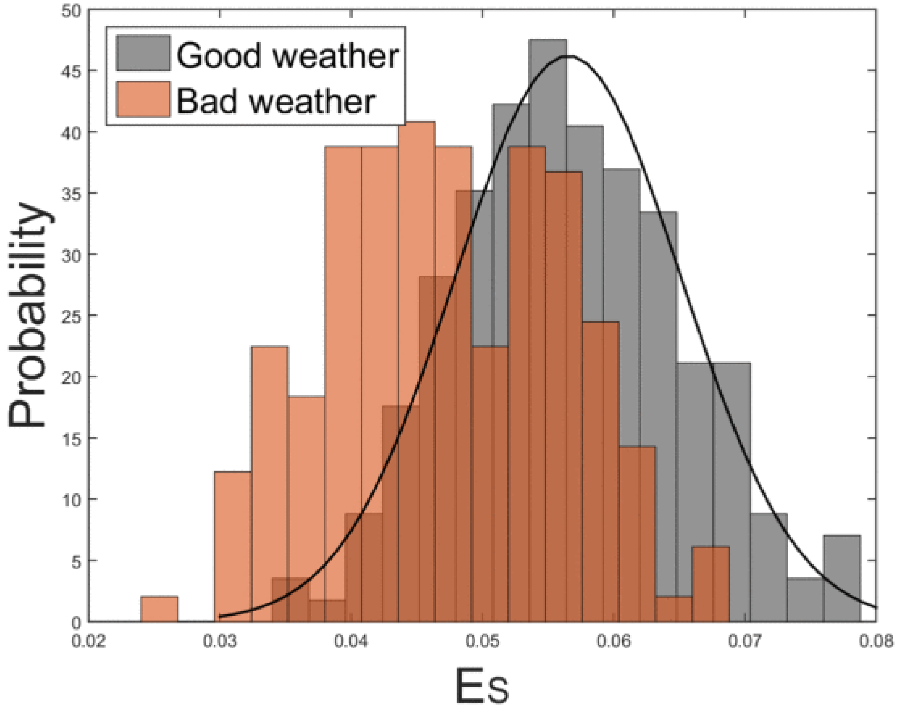


Feature B: Transform Domain Entropy (ES)

- **Step:** Apply a Haar Wavelet Transform to decompose the saturation map into different scales and orientations (vertical, horizontal, diagonal). Then, calculate the entropy of these wavelet coefficients.

- **Reason:** Natural images possess specific statistical structures in the frequency domain (e.g., edges and textures). Pollution blurs these details.

- **Observation:** The distribution of these entropy values for clear-weather images follows a Gaussian Distribution.



The model asks: **"How likely is it that this image was taken in clear weather?"**

Step: The model compares the extracted features (HS and ES) against pre-built "Naturalness Statistics" (NS) models.

These NS models were built using 5,000+ clean images to define what "clean" mathematically looks like.

Calculation:

- Calculate probability QV using the Extreme Value density function (for spatial feature).
- Calculate probability QG using the Gaussian density function (for transform feature).
- Combine them into a single "Quality" or "Naturalness" score Q.

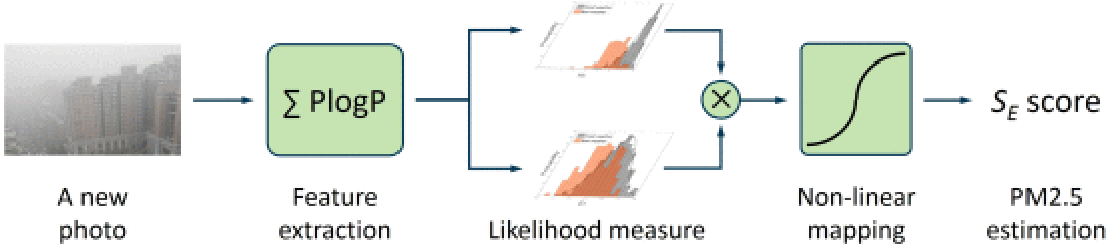
Reason: A high Q score means the image fits the "clean weather" profile perfectly (Low PM2.5). A low Q score means the statistical structure is broken (High PM2.5).

Nonlinear Mapping

The final step converts the abstract "Naturalness Score" into a concrete PM2.5 concentration number.

Step: Feed the combined score Q into a logistic function (a simple S-shaped curve).

Reason: The relationship between image degradation and PM2.5 concentration is not perfectly linear. A logistic function accurately maps the "naturalness likelihood" to the actual PM2.5 value, handling the saturation points where air is extremely clean or extremely polluted.



Basic flowchart to illustrate how to use the PPPC predictor to estimate PM2.5 concentration.

- **Paper DOI:** 10.1016/j.atmosenv.2021.118623

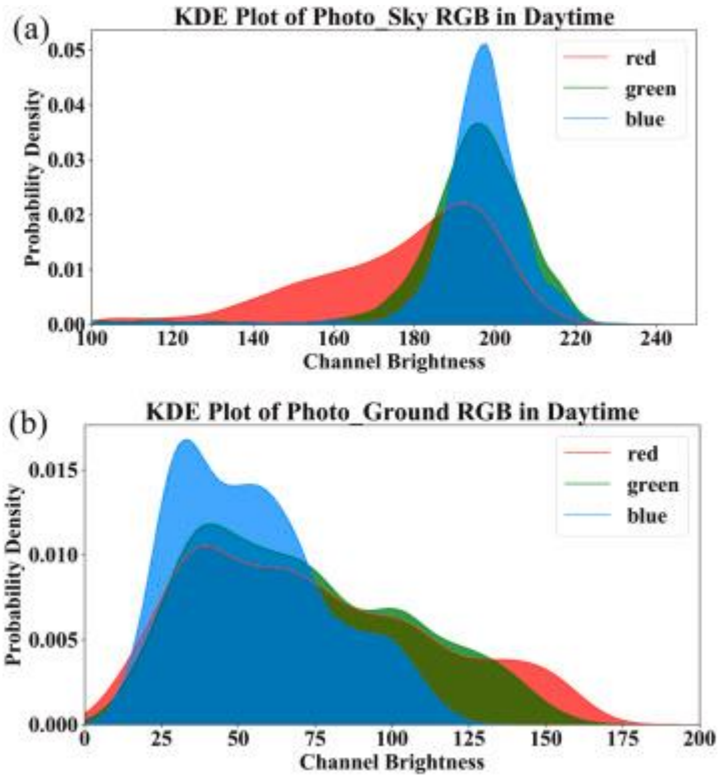
Hypothesis: Colour features in photographs reflect atmospheric transparency and can serve as a proxy for PM2.5 concentration, comparable to or complementing boundary layer height measurements.

- Photos: Auto-camera on IAP rooftop, Beijing (sampling every 30 min)
- Ground truth PM2.5: Official air quality data from Olympic Sports Centre (2 km away)
- Weather data: ERA5 reanalysis (vertical temperature, wind, pressure layers)

Each photo is divided into TWO PARTS:

- Sky part (top 50% of image)
- Ground part (bottom 50% of image)

For each part, the average brightness of Red, Green, and Blue channels are calculated.



Finding: Probability distributions of R and B are significantly different in both parts.

Conclusion: B/R ratio is the most representative feature, not B/G or G/R.

Physical Processes Differ by Time of Day

Day-time:

- Driven by solar radiation. The sun strongly affects air mixing, light scattering, and therefore how photographic features relate to air pollution.
- Blue light dominates sky color (Rayleigh scattering); haze and PM2.5 affect the blue-red ratio.
- Strong turbulence and convective mixing often disperse pollutants vertically.

Night-time:

- No direct sunlight. Artificial lights become the main “illumination” in photos.
- Atmospheric stability increases; pollutants can accumulate near the ground under weak vertical mixing (temperature inversion).
- Photographic features like RGB brightness relate differently to PM2.5 because artificial lights and streetlights illuminate the atmosphere, not the sun.

Statistical Patterns Differ

- Night-time PM2.5 often has a more uniform and sometimes higher concentration because stagnant air prevents dispersion.
- Day-time PM2.5 is more variable, with sharp peaks during pollution events and cleaner periods when the boundary layer is high.

Final Input Variables

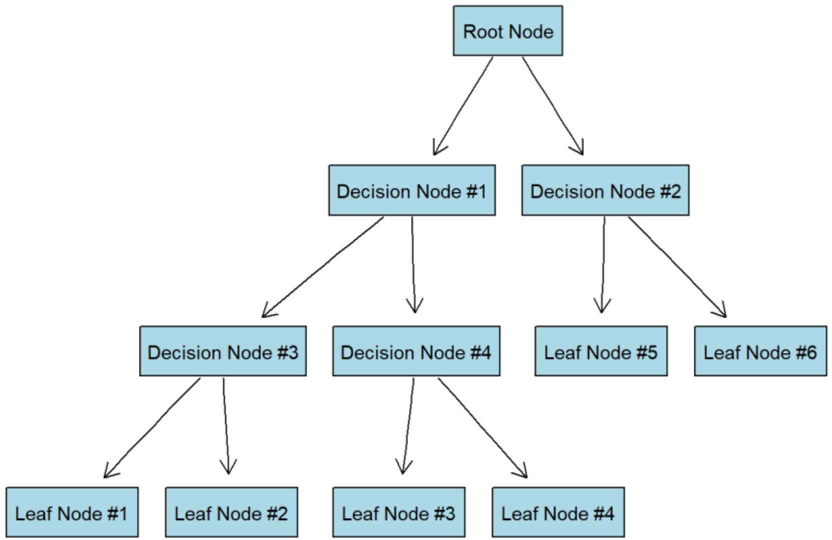
- B/R_sky ← Photo feature
- RGB_sky ← Photo feature
- B/R_ground ← Photo feature
- RGB_ground ← Photo feature

- BLH - Boundary Layer Height (m)
- KE_850 - Kinetic Energy at 850 hPa
- GE_500 - Gravitational Potential Energy at 500 hPa
- T2m - Temperature at 2m (surface temperature)

- U10 - Wind component (East-West) at 10m
- V10 - Wind component (North-South) at 10m
- TP - Total Precipitation (mm)
- SP - Surface Pressure (Pa)

CART Algorithm Flow:

1. Start with Root Node - Contains all training data
2. Evaluate All Possible Splits - For each feature, test every possible split point
3. Select Best Split - Choose the split that best reduces impurity (classification) or minimizes residual error (regression)
4. Recursive Partitioning - Apply the same process to each child node
5. Stop Growing - When a stopping criterion is met (max depth, minimum samples in leaf, no improvement possible)
6. Prune the Tree - Remove branches that don't improve generalization



Machine Learning Model

Tree depth:

Maximum depth = 6 (> 6 → overfitting)

Splitting criterion:

Standard CART regression → splits chosen by minimizing mean squared error (MSE) on PM2.5

Day-time CART

- ✓ Test R^2: ≈ 0.50
- ✓ Test RMSE: ≈ 29 μg/m³
- ✓ Root node threshold: B/Rsky = 1.14

Night-time CART

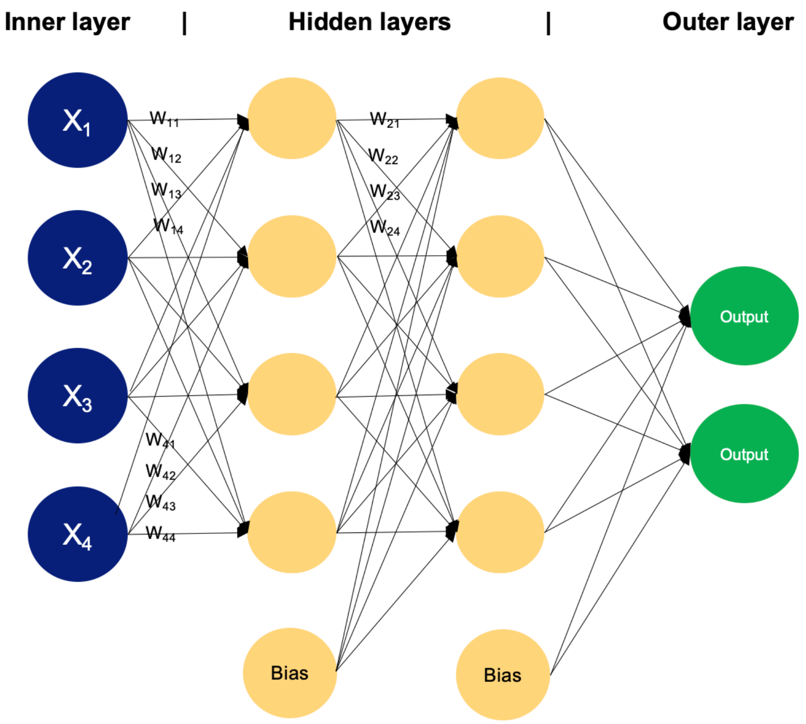
- ✓ Test R^2: ≈ 0.50
- ✓ Test RMSE: ≈ 20 μg/m³
- ✓ Root node: low vs high RGBsky, with BLH used very early in the splits.

An MLP is a type of artificial neural network composed of:

- An input layer (takes input features),
- One or more hidden layers (intermediate processing layers),
- An output layer (produces prediction).

Each layer has nodes (neurons), and every node in one layer connects to all nodes in the next layer via weighted connections.

Unlike simple linear models, MLPs apply nonlinear activation functions in the hidden layers (like ReLU or sigmoid), enabling them to learn complex, nonlinear patterns in data.



Machine Learning Model

Network architecture:

- Three hidden layers
- Each hidden layer has 3 neurons (total: 9 hidden neurons)
- Input: All 12 features (both photo-based and meteorological)
- Separate MLPs trained for day-time and night-time data, as with CART

Training process:

- Data normalized for NN input
- 70/30 train/test split (same as CART)
- Trained for 30 iterations (fast convergence)
- Standard backpropagation and error minimization

For both Day and Night: **RMSE ≈3 μg/m³**

Black-box approach: maximize predictive accuracy, not interpretability.

Machine Learning Results:

- ✓ Neural network (MLP): High accuracy in PM2.5 estimation (RMSE: 1–3 μg/m³), but the method is a black box—not interpretable for cause-and-effect relationships.
- ✓ Decision tree: Larger error (an order of magnitude higher), but transparent and interpretable—you can quantify which image features matter most.

Day-time:

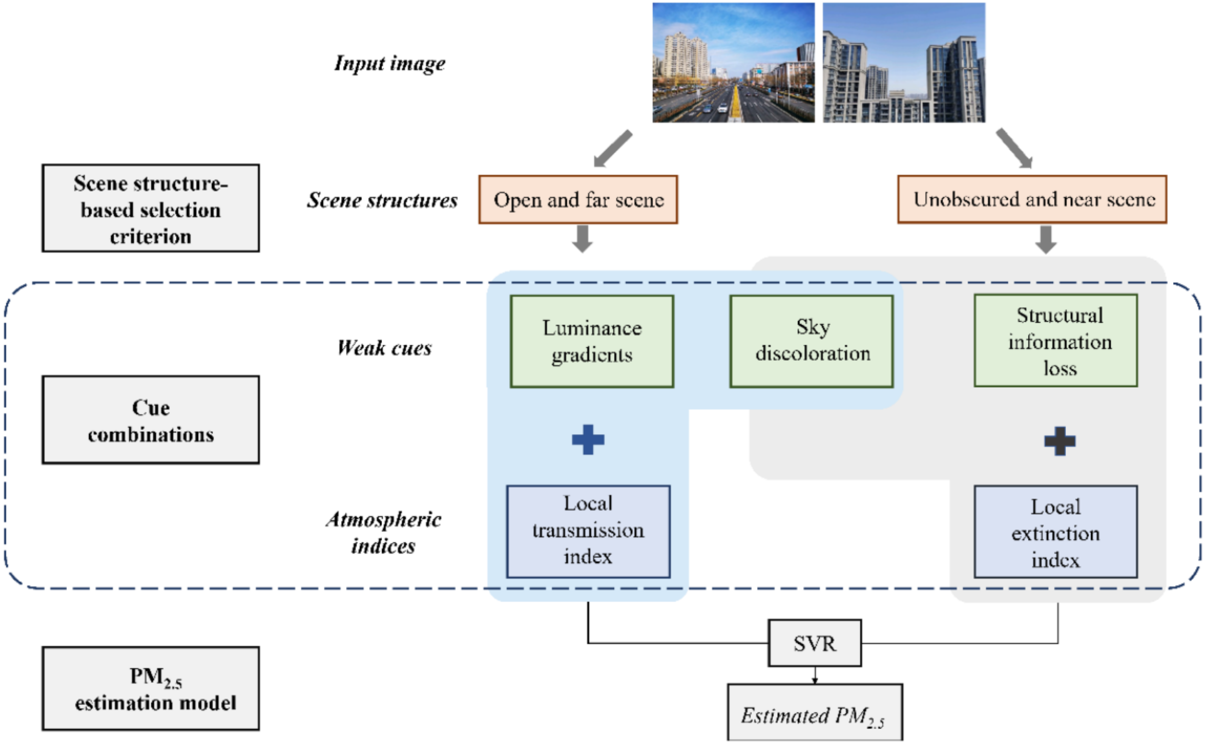
- ✓ B/Rsky is the most important predictor for PM2.5 in decision tree models (even more than meteorological variables like boundary layer height, BLH).

Night-time:

- ✓ BLH takes priority, but B/Rsky remains comparably important in the tree’s structure.

Hybrid Approach

- **Paper DOI: 10.3390/rs14112572**



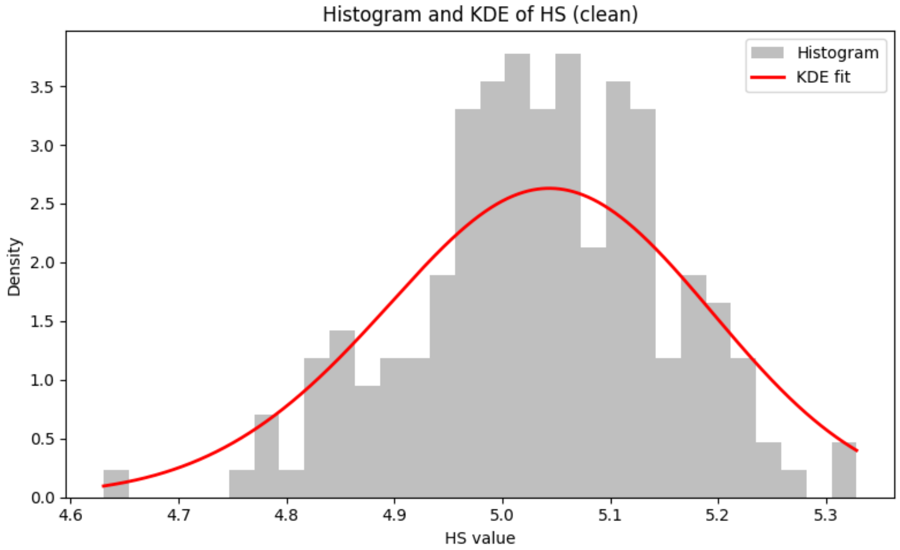
Workflow of the hybrid $PM_{2.5}$ concentration estimation framework.

Best Results:

- ✓ R^2: ≈ 0.90
- ✓ RMSE: ≈ 36 μg/m³

RGB: 20250206-0900.jpg vs 20250422-0900.jpg


Saturation: 20250206-0900.jpg vs 20250422-0900.jpg


Histogram and KDE of HS (clean)
Histogram
KDE fit
Density
0.0
0.5
1.0
1.5
2.0
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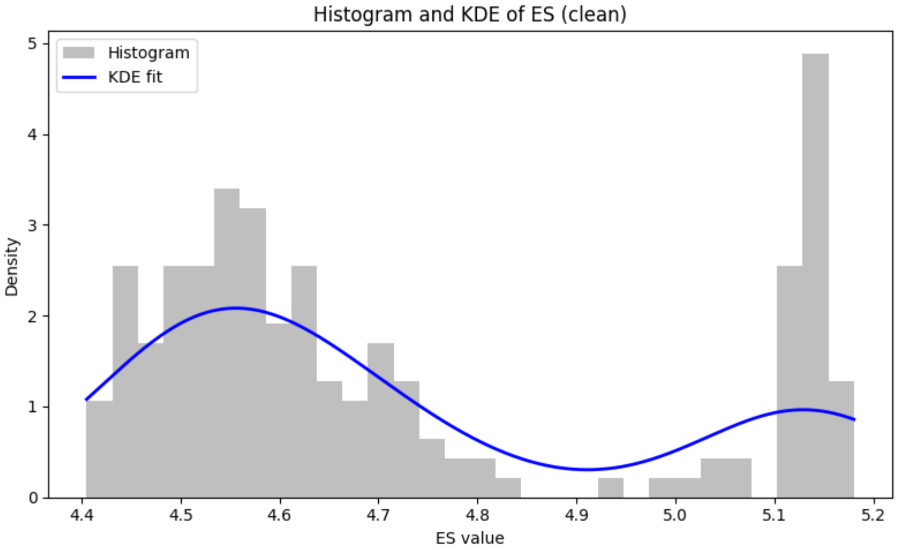
5.2
5.3
HS value


Histogram and KDE of ES (clean)
Histogram
KDE fit
Density
0
1
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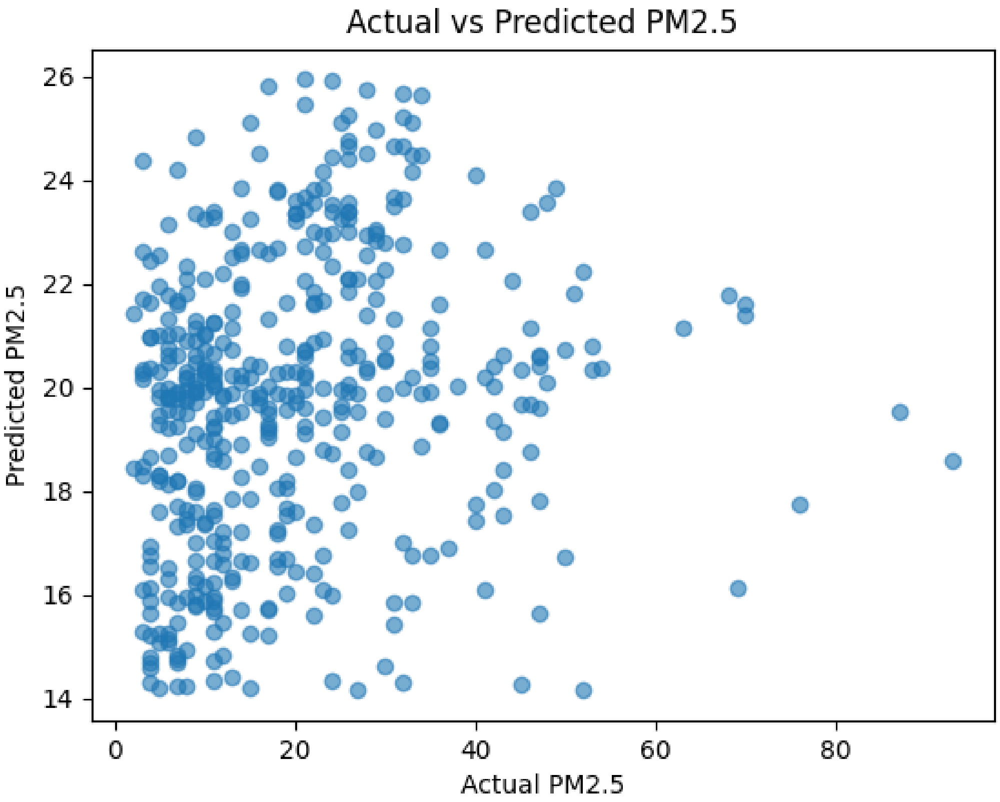
ES value


Actual vs Predicted PM2.5
Predicted PM2.5
26
24
22
20
18
16
14
0
20
40
60
80
Actual PM2.5

Conclusion

- Utilizing images from webcams and cellphones to estimate PM2.5 concentrations is becoming more attractive.
- This is mainly because conventional sensor-based approaches are expensive and provide limited spatial coverage.
- Research efforts use a broad range of methods, from **physics-based models to machine learning, deep learning, and hybrid approaches that combine these techniques**.
- Deep learning and complex models often give the **best** prediction results.
- However, these high-performing models come with **interpretability** challenges—it's not always clear whether correlations are meaningful or influenced by confounding variables.
- Physical models are easier to interpret.
- But they are less accurate compared to advanced statistical or machine learning methods.
- The intended **toolkit** will let users select or customize methods according to their needs—ranging from simple to advanced.
- **Large datasets** are critical for training more accurate and robust models, especially as model complexity increases.

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