

# Digital Health for Climate Resilience

## Lecture 3

# Environmental Monitoring Technologies and Digital Tools



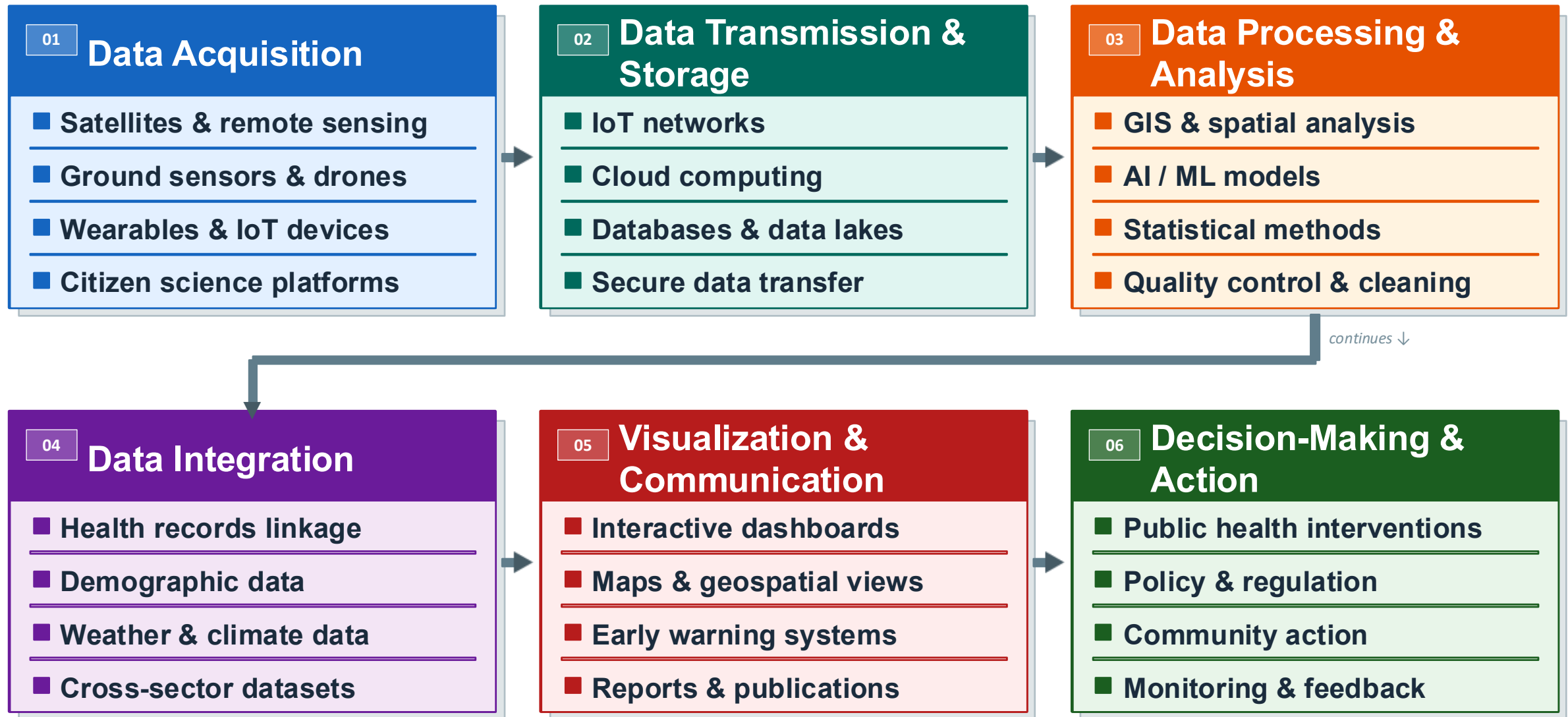
# Lecture Outline

- **The Evolution of Environmental Monitoring:** From Sparse to Hyperlocal
- **Conceptual Framework:** The Data Pipeline for Environmental Health
- **Satellite-Based Remote Sensing:** Seeing the Planet from Above
- **Ground-Based Monitoring:** Reference Stations to Low-Cost Sensors
- **Geographic Information Systems (GIS) and Spatial Analysis**
- **The Internet of Things (IoT) and Real-Time Surveillance**
- **Personal Exposure Monitoring:** Wearables and Mobile Health
- **Unmanned Aerial Vehicles (UAVs/Drones)**
- **Big Data, AI, and Machine Learning in Exposure Science**
- **Data Integration and Visualization Platforms**
- **Case Studies in Action**
- **Challenges and Limitations**
- **Conclusion and Key Takeaways**

# The Evolution of Environmental Monitoring

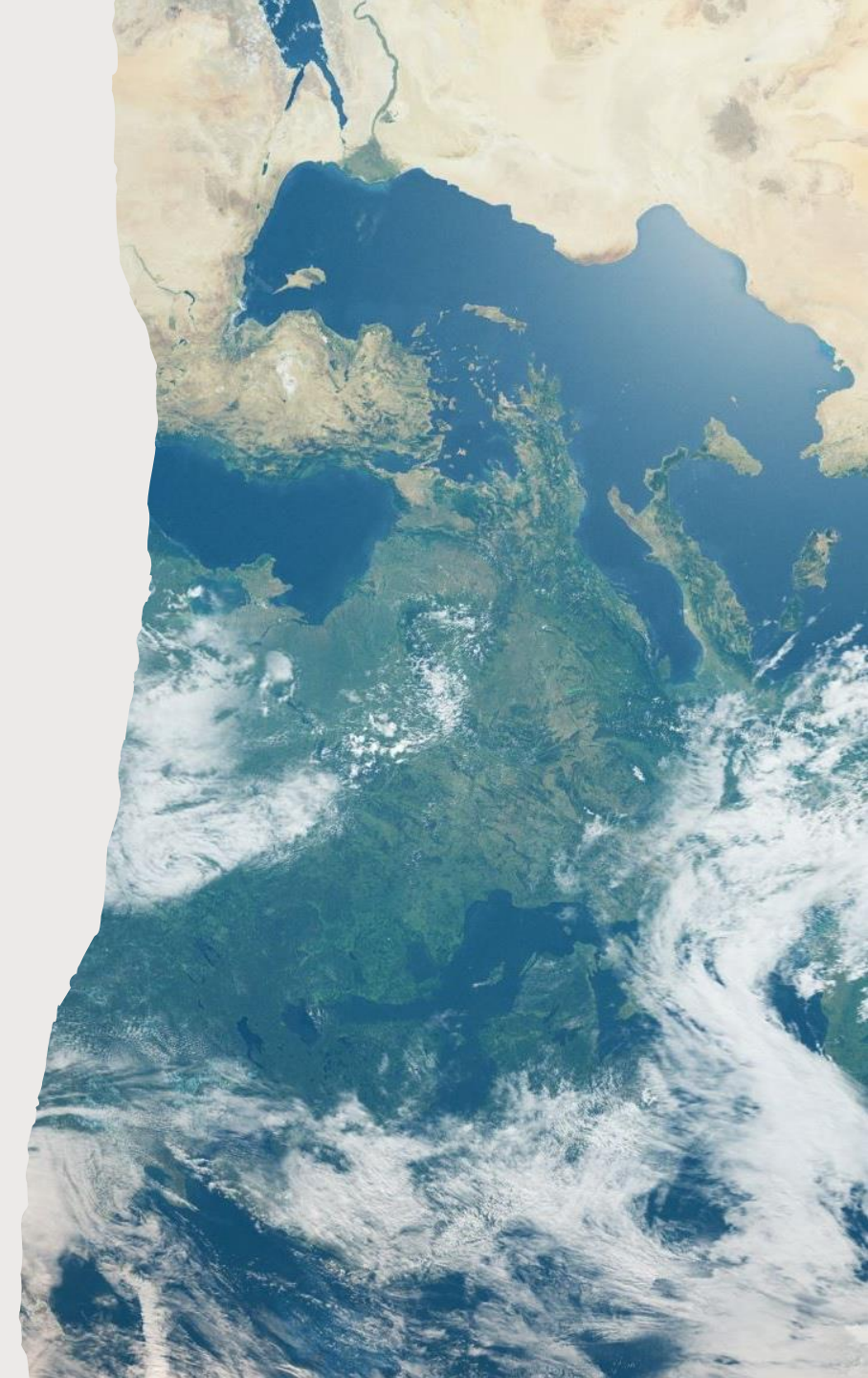
- **Traditional Approach:**
  - Sparse network of expensive, reference-grade monitoring stations
  - Operated by government agencies
  - High data quality but limited spatial coverage
  - Data often released with significant time lags
  - Effectively "blind" in most of the world
- **The New Paradigm:**
  - Dense networks of low-cost sensors
  - Satellite data providing global coverage
  - Real-time data transmission
  - Citizen science and community monitoring
  - Integration of diverse data streams
- **Result:** A fundamental shift from data scarcity to data abundance

# Conceptual Framework: The Data Pipeline for Environmental Health



# Satellite-Based Remote Sensing

- **Principle:** Sensors on satellites measure reflected or emitted radiation from the Earth's surface and atmosphere
- **Key Applications in Environmental Health:**
  - **Aerosol Optical Depth (AOD):** Used to estimate ground-level PM2.5 concentrations, especially where ground monitors are absent
  - **Land Surface Temperature (LST):** Maps heat distribution across cities to identify urban heat islands
  - **Vegetation Indices (NDVI):** Identifies areas of vegetation, used for malaria risk modeling and drought monitoring
  - **Water Quality:** Detects algal blooms, sediment plumes, and temperature changes in water bodies
  - **Land Use/Land Cover:** Maps urbanization, deforestation, and agricultural expansion
- **Advantages:** Global coverage, consistent measurements, long-term archives
- **Limitations:** Coarse spatial resolution for some sensors, atmospheric interference, need for ground validation





# Ground-Based Monitoring: The Reference Standard

- **Reference-Grade Monitors:**
  - Operated by regulatory agencies (e.g., EPA, DEFRA)
  - Use standardized methods (e.g., Federal Reference Methods)
  - Provide highly accurate, legally defensible data
  - **Limitations:** Very expensive to purchase and maintain, sparse spatial coverage
- **Low-Cost Sensors:**
  - Use newer technologies (e.g., optical particle counters for PM, metal oxide sensors for gases)
  - Cost a fraction of reference monitors (e.g., \$100-\$2000 vs. \$20,000+)
  - Enable dense, community-based monitoring networks
  - **Critical Challenge:** Data quality is highly variable; sensors are susceptible to environmental factors (humidity, temperature) and drift over time
  - **Requirement:** Must be calibrated against reference monitors, often requiring co-location studies

# Geographic Information Systems (GIS) and Spatial Analysis

- **GIS:** A system for capturing, storing, analyzing, and managing spatial or geographic data
- **Core Functions:**
  - **Mapping and Visualization:** Creating maps of environmental exposures and health outcomes.
  - **Spatial Queries:** Identifying features within a certain distance (e.g., homes within 500m of a highway)
  - **Buffer Analysis:** Creating zones around features (e.g., around a polluting facility)
  - **Overlay Analysis:** Combining multiple data layers (e.g., pollution + demographics + health data)
  - **Spatial Interpolation:** Estimating values at unsampled locations (e.g., Kriging, Inverse Distance Weighting)
- **Advanced Spatial Methods:**
  - **Spatial Cluster Detection:** Statistical tests to identify if cases are clustered in space (e.g., Kulldorff's spatial scan statistic)
  - **Land Use Regression (LUR):** Uses predictor variables (traffic, land use) to model pollution surfaces at high resolution

# The Internet of Things (IoT) and Real-Time Surveillance

- **IoT Defined:** A network of physical devices ("things") embedded with sensors, software, and network connectivity, allowing them to collect and exchange data
- **Application to Environmental Health:**
  - Networks of low-cost sensors transmitting real-time air quality, noise, temperature, and humidity data
  - Smart water quality monitoring systems
  - Connected weather stations
- **Key Advantages:**
  - **Real-Time Data:** Enables immediate public health action (e.g., alerting vulnerable individuals during a pollution spike)
  - **High Temporal Resolution:** Captures variations throughout the day, not just daily averages
  - **Dense Spatial Coverage:** Can deploy many nodes across a city
- **Challenges:**
  - Data management and storage (big data)
  - Power supply for remote sensors
  - Network connectivity in low-resource settings
  - Ensuring data quality across thousands of devices

# Personal Exposure Monitoring: Wearables and Mobile Health

- **The Problem:** Traditional monitoring at fixed sites does not capture what individuals are actually exposed to as they move through different microenvironments (home, work, commute, school)
- **The Solution:** Personal exposure monitoring
  - **Portable Sensors:** Small, battery-powered devices that individuals carry or wear to measure pollutants (PM, black carbon, noise)
  - **Wearable Biomonitoring:** Smartwatches and fitness trackers that measure physiological responses (heart rate, activity, sleep)
  - **GPS Trackers:** Record location, allowing exposure to be linked to specific places and activities
  - **Mobile Apps:** Enable real-time symptom logging and exposure reporting
- **Integration:** Combining personal sensor data, GPS tracks, and physiological data allows for powerful analyses linking **dynamic exposures** to **acute health effects**
- **Example:** A study of asthma could have participants carry a personal PM monitor and wear a smartwatch while logging symptoms in an app, revealing the precise triggers for an individual's asthma attacks

# Unmanned Aerial Vehicles (UAVs/Drones)



- **Capabilities:**
  - Equipped with cameras (visible, multispectral, thermal) and miniaturized sensors
  - Can fly at low altitudes, below cloud cover
  - Can access remote or hazardous areas
  - Provide very high spatial resolution imagery
- **Applications in Environmental Health:**
  - **Mapping Mosquito Breeding Habitats:** Using multispectral imagery to identify standing water and vegetation
  - **Monitoring Industrial Emissions:** Flying through plumes to measure pollutant concentrations
  - **Disaster Response:** Assessing damage after floods, hurricanes, or wildfires
  - **Mapping Urban Heat:** Using thermal cameras to identify hot spots
  - **Precision Agriculture:** Monitoring crop health and water stress
- **Advantages:** On-demand deployment, high resolution, access to difficult terrain
- **Limitations:** Regulatory restrictions, limited battery life, skilled operator required, payload weight limits

# Big Data, AI, and Machine Learning

- **The Data Challenge:** We now have massive, diverse datasets from satellites, sensors, wearables, and health records. Traditional statistical methods struggle to find patterns in such high-dimensional, complex data
- **The AI/ML Solution:**
  - **Machine Learning Algorithms** (e.g., random forests, gradient boosting, neural networks) can learn complex, non-linear relationships from data
  - **Applications:**
    - **Predicting Pollution Surfaces:** Using ML to integrate satellite, land use, and traffic data for high-resolution exposure models
    - **Forecasting Disease Outbreaks:** Predicting malaria or dengue risk based on climate and environmental drivers
    - **Source Apportionment:** Identifying the sources of pollution (e.g., traffic vs. industry) from sensor data
    - **Anomaly Detection:** Identifying unusual events (e.g., a chemical spill) from real-time sensor streams
    - **Image Analysis:** Automatically identifying mosquito breeding habitats from drone or satellite imagery
- **Key Point:** ML is a powerful tool for pattern recognition and prediction, but models must be carefully validated and their assumptions understood

# Data Integration and Visualization Platforms

- **The Silo Problem:** Environmental data, health data, meteorological data, and demographic data are often held by different agencies in incompatible formats
- **The Solution:** Integrated platforms that bring these diverse data streams together
- **Examples:**
  - **DHIS2 Climate App:** Integrates climate data (from global gridded datasets) with health data in the DHIS2 platform used by many LMICs
  - **WHO Environmental Health Inequalities Platform:** Integrates environmental and health data to track inequalities
  - **City-Level Dashboards:** Real-time visualizations of air quality, heat, and health alerts for public and policymakers (e.g., Plume Labs, AirNow)
  - **Health Information Systems:** Integrating environmental alerts into early warning systems for diseases
- **Key Functions:**
  - Data harmonization and standardization
  - Interactive visualization (maps, time series, dashboards)
  - Alerting and notification
  - Data download for research

# Case Study 1: Mapping Air Pollution in Data- Sparse Regions

- **Challenge:** In Sub-Saharan Africa, there are very few ground-based air quality monitors, making it impossible to assess population exposure for health studies
- **Solution:** Use satellite-derived Aerosol Optical Depth (AOD) combined with chemical transport models and machine learning to estimate ground-level PM2.5 concentrations
- **Process:**
  - Obtain daily AOD data from satellites (e.g., MODIS, MISR)
  - Use a model (e.g., GEOS-Chem) to simulate the relationship between AOD and surface PM2.5
  - Apply machine learning to integrate additional data (land use, population meteorology) and improve resolution
  - Validate against any available ground data (e.g., from short-term campaigns)
- **Outcome:** High-resolution (e.g., 1km x 1km) maps of annual and daily PM2.5 for the entire continent, enabling GBD estimates and health studies

# Case Study 2: Dengue Early Warning System Using Climate and IoT Data

- **Challenge:** Dengue outbreaks strain health systems; early warning could enable proactive vector control
- **Solution:** An integrated system combining climate forecasts, IoT weather station data, and mosquito surveillance
- **Process:**
  - **Data Acquisition:** Network of IoT-enabled weather stations provides real-time temperature, humidity, and rainfall data
  - **Satellite Data:** Provides vegetation indices (NDVI) and land surface temperature
  - **Modeling:** Machine learning model integrates these data to predict mosquito abundance and dengue transmission risk, based on known temperature-dependent dynamics (e.g., extrinsic incubation period)
  - **Alert Generation:** When risk exceeds a threshold, an alert is sent to health authorities
  - **Action:** Vector control teams are deployed for targeted spraying and source reduction before the outbreak peaks
- **Outcome:** Shift from reactive outbreak response to proactive, targeted prevention

# Challenges and Limitations

- **Data Quality and Calibration:** Low-cost sensors require rigorous calibration; satellite data needs ground validation
- **Data Integration and Interoperability:** Different data formats, standards, and ownership create silos
- **Data Volume and Management:** "Big data" requires significant storage, processing power, and analytical expertise
- **Privacy and Ethics:** Personal exposure monitoring and GPS tracking raise serious privacy concerns
- **Representativeness and Bias:** Data from wearables and smartphone apps may not represent the general population; low-cost sensor networks may be denser in wealthier areas
- **The "Black Box" Problem:** Complex ML models can be difficult to interpret, making it hard to understand *why* a prediction is being made
- **Digital Divide:** The benefits of these technologies are not equally distributed; low-income countries and communities may lack the infrastructure, expertise, and resources to deploy and use them

# Conclusion and Key Takeaways

- **Environmental monitoring has undergone a revolution**, shifting from sparse, delayed data to dense, real-time, and hyperlocal information
- **A diverse toolkit is now available**, including satellites, low-cost sensors, GIS, IoT, wearables, drones, and AI/ML
- **Integration is key**: The true power lies in combining these technologies and linking environmental data with health, demographic, and meteorological data
- **These tools enable a paradigm shift** from reactive public health (responding to outbreaks) to proactive, predictive, and personalized interventions
- **Data quality, privacy, equity, and the digital divide are critical challenges** that must be addressed to ensure these tools benefit all populations
- **For public health professionals, understanding these technologies is essential** for designing studies, interpreting evidence, and advocating for evidence-based policies in a rapidly changing world

# Q&A / Discussion

**Thank you.**

**Questions?**

- How can we ensure equitable access to these technologies globally?
- What are the most promising emerging technologies you see?
- How do we balance the benefits of real-time data with privacy concerns?

# References

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