Towards Tracking the Emissions of Every Power Plant on the Planet

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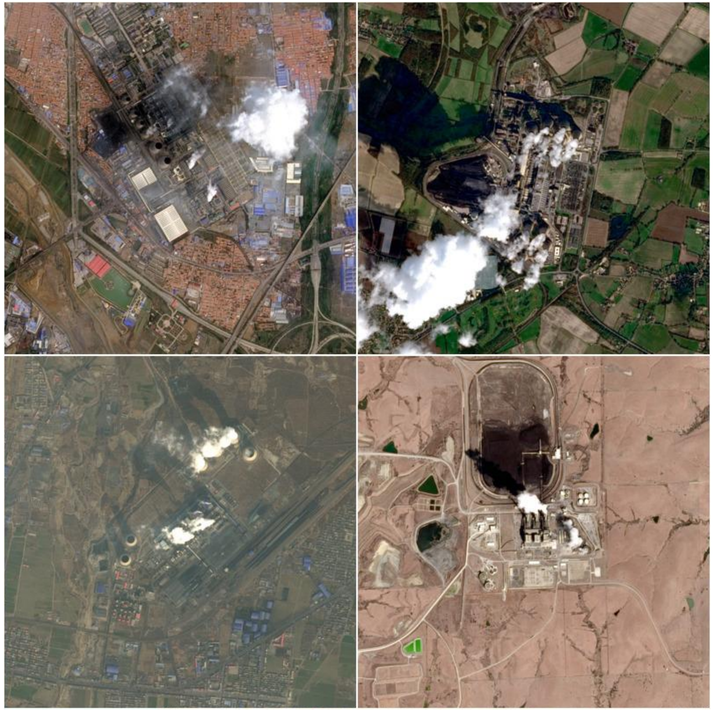
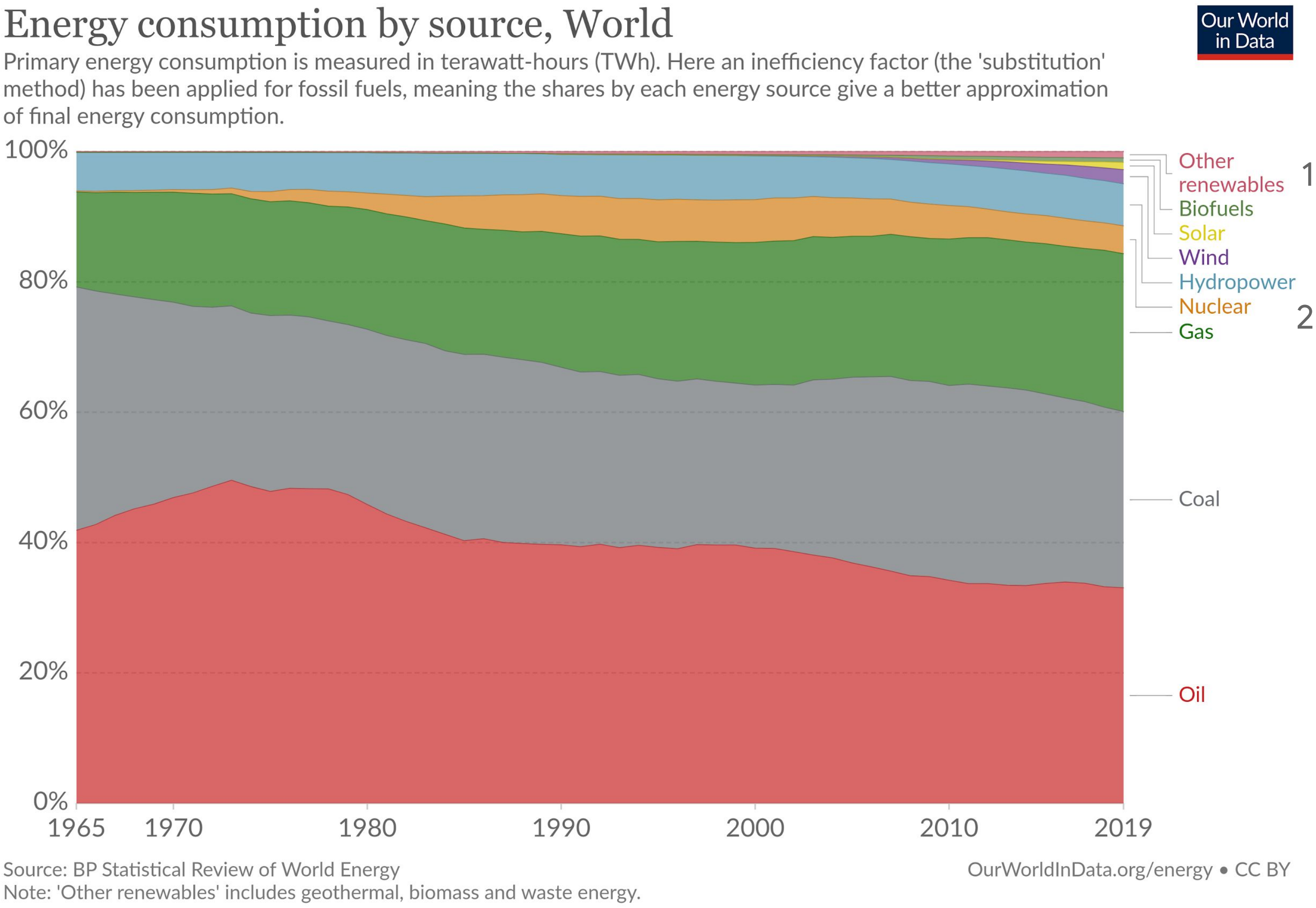
WattTime[1], Energy & Clean Air Analytics[2], Carbon Tracker[3], Google.org[4], Pixel Scientia Labs[5], Georgetown University[6]





Fossil Fuel Power Plants

1. **30%** of global GHG emissions
2. **85%** of global electricity generation

Global Coal Power

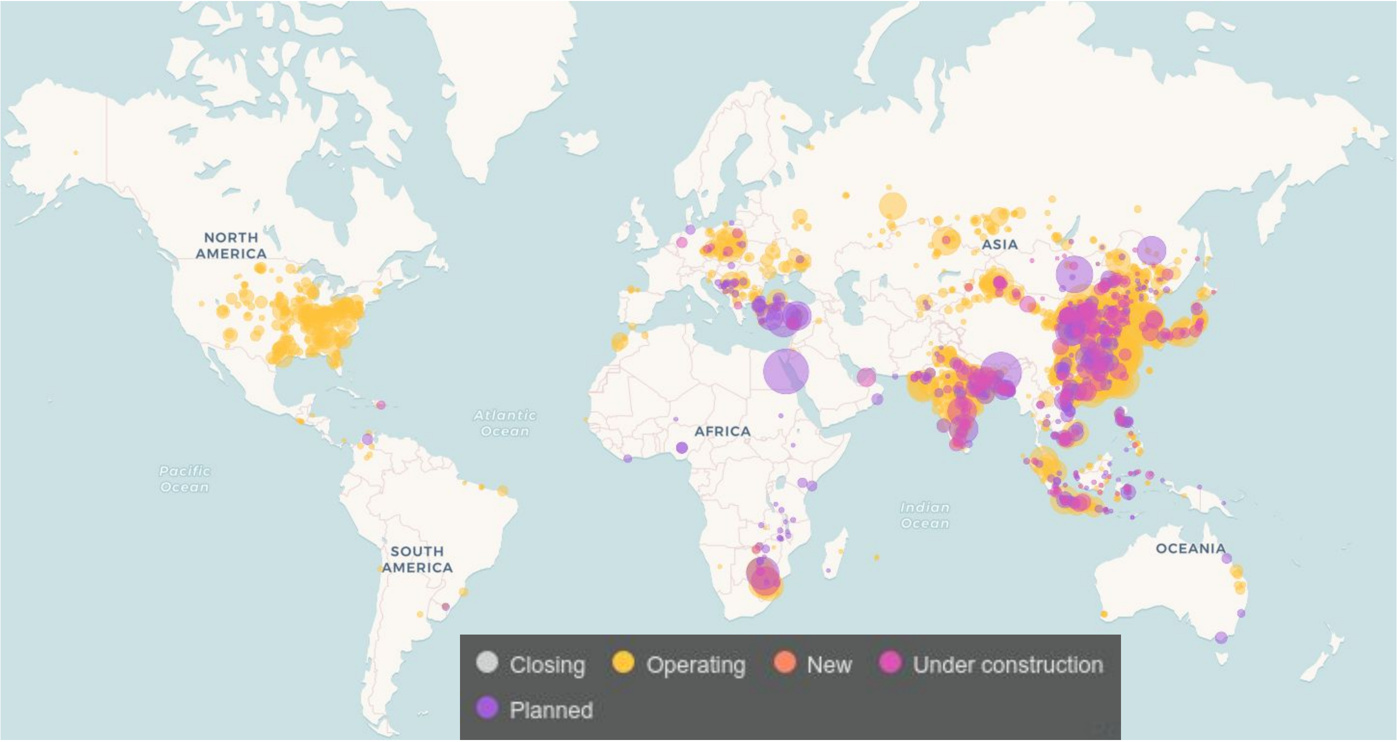


Image credit: https://www.carbonbrief.org/mapped-worlds-coal-power-plants

Fossil Fuel Power Plants

1. **30%** of global GHG emissions
2. **85%** of global electricity generation
3. **Decreasing** in many parts of the world; **increasing** in others
4. Critical to understand these **sources** of emissions

Satellite images
+
Machine learning

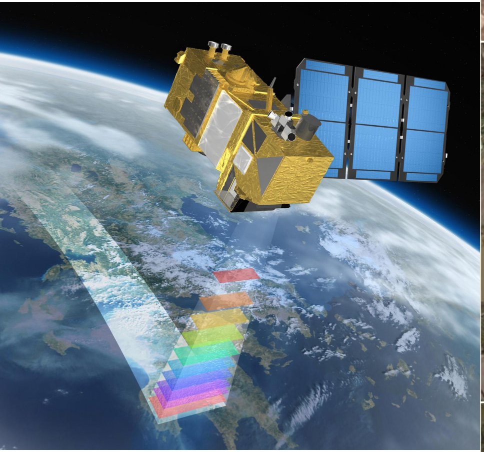


Image credit: ESA

Image credit: Airbus SPOT

Emissions estimates will be made public

Identify optimal locations for new wind or solar farms

Enable new or updated environmental policy

See how much local power plants contribute to climate change

Track progress toward Paris Climate Agreement

Image credits: Pixabay, Unsplash

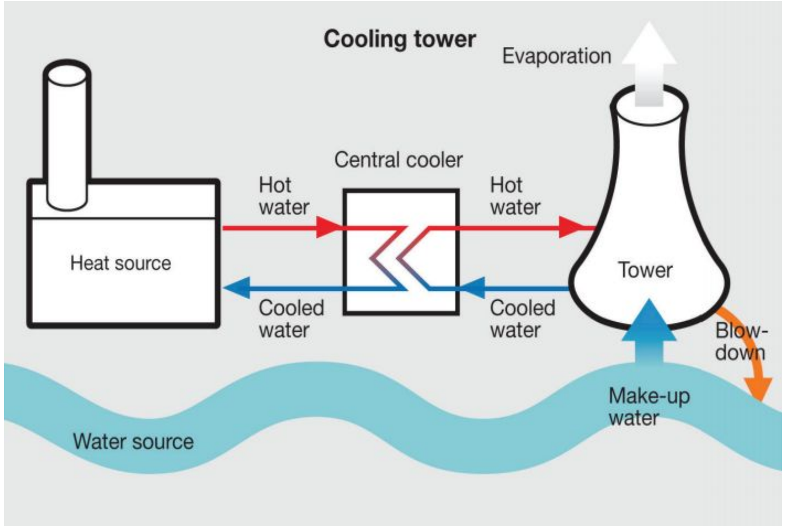
CO_2 is measured globally by two satellites: OCO-2 and GOSAT

Image credits: Orbiting Carbon Observatory-2 (OCO-2) Watching the Earth Breathe…Observing CO2 from Space

Power plants emit GHGs through a chimney

Imagery source: National Agricultural Imagery Program

Other operational signs are visible depending on the cooling technology



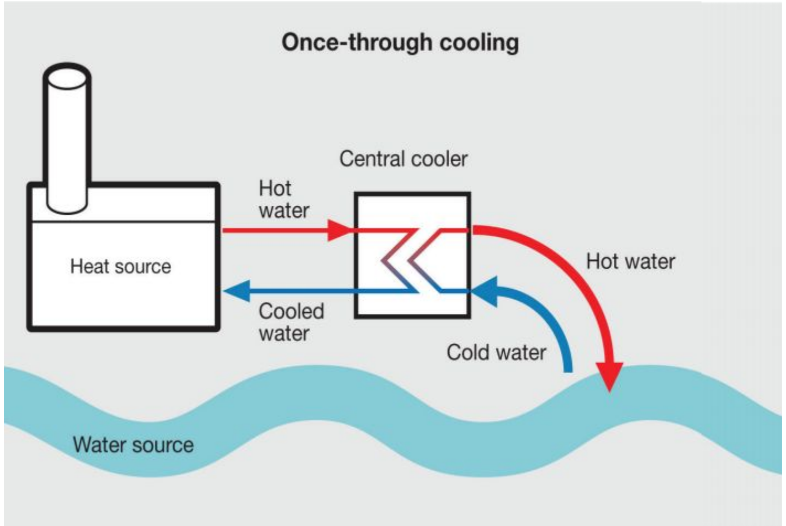
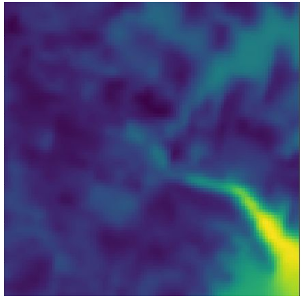


Image credit: Efficient Use and Consumption of Water in Power Generation



Thermal infrared

We created a ground truth dataset by joining multiple sources

Geolocation: Global Power Plant Database and Global Coal Plant Tracker

Plant fuel type, capacity, cooling technology: S&P Global Platts’ World Electric Power Plants Database

Hourly power generation data: AMPD (US), ENTSOE (Europe), AEMO (Australia)

Starting with a simple setup: predicting on or off from a single image

We annotated cooling towers and flue stacks to focus our models

Annotate with Open Street Map

Mechanical/natural draft plant

Extract patches from satellite image

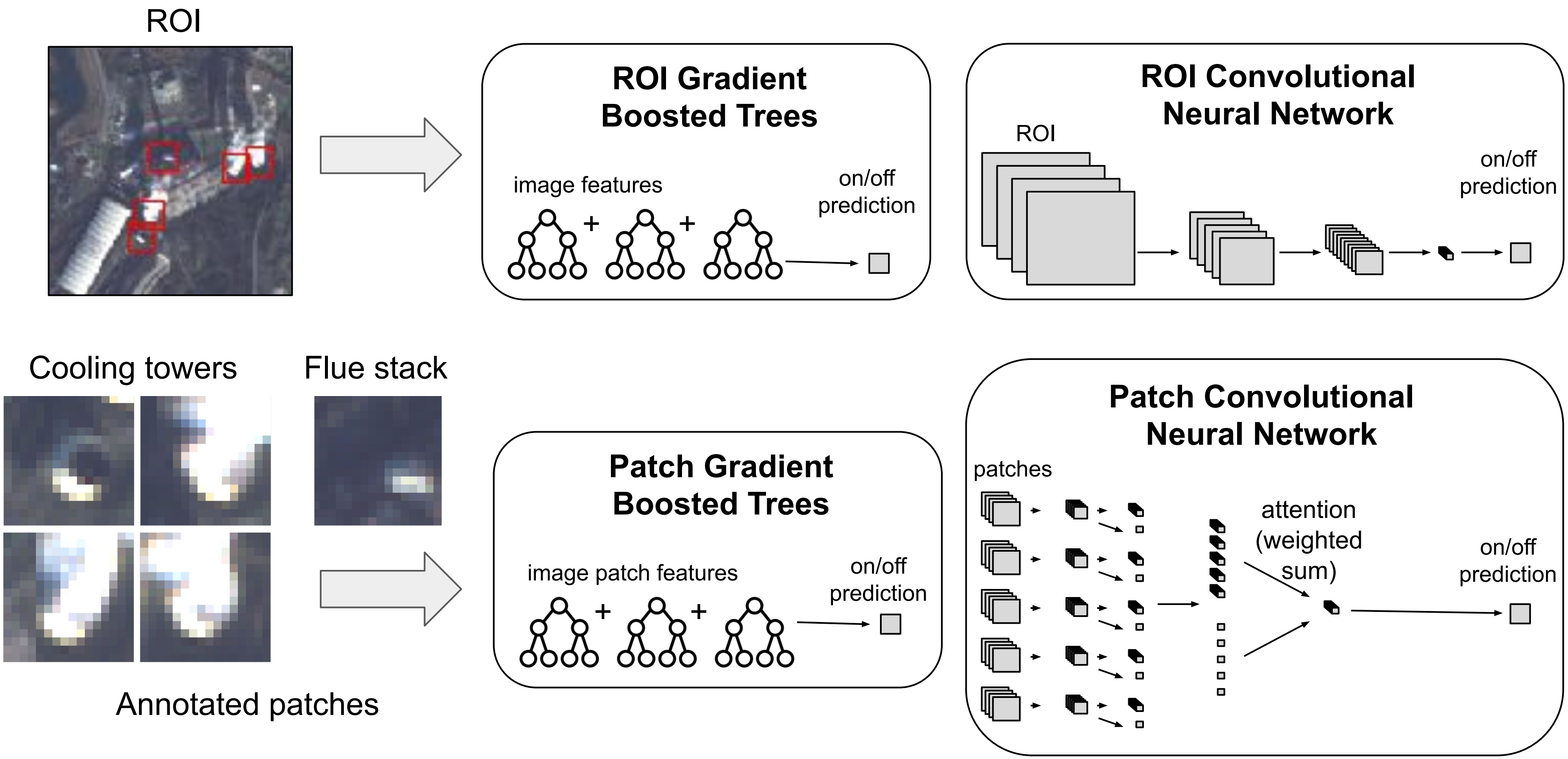
ROI

Cooling towers

Flue stack

Annotated patches

We trained 4 different types of models



Patch CNN models were successful for mechanical/natural draft
Once-through plants are still challenging

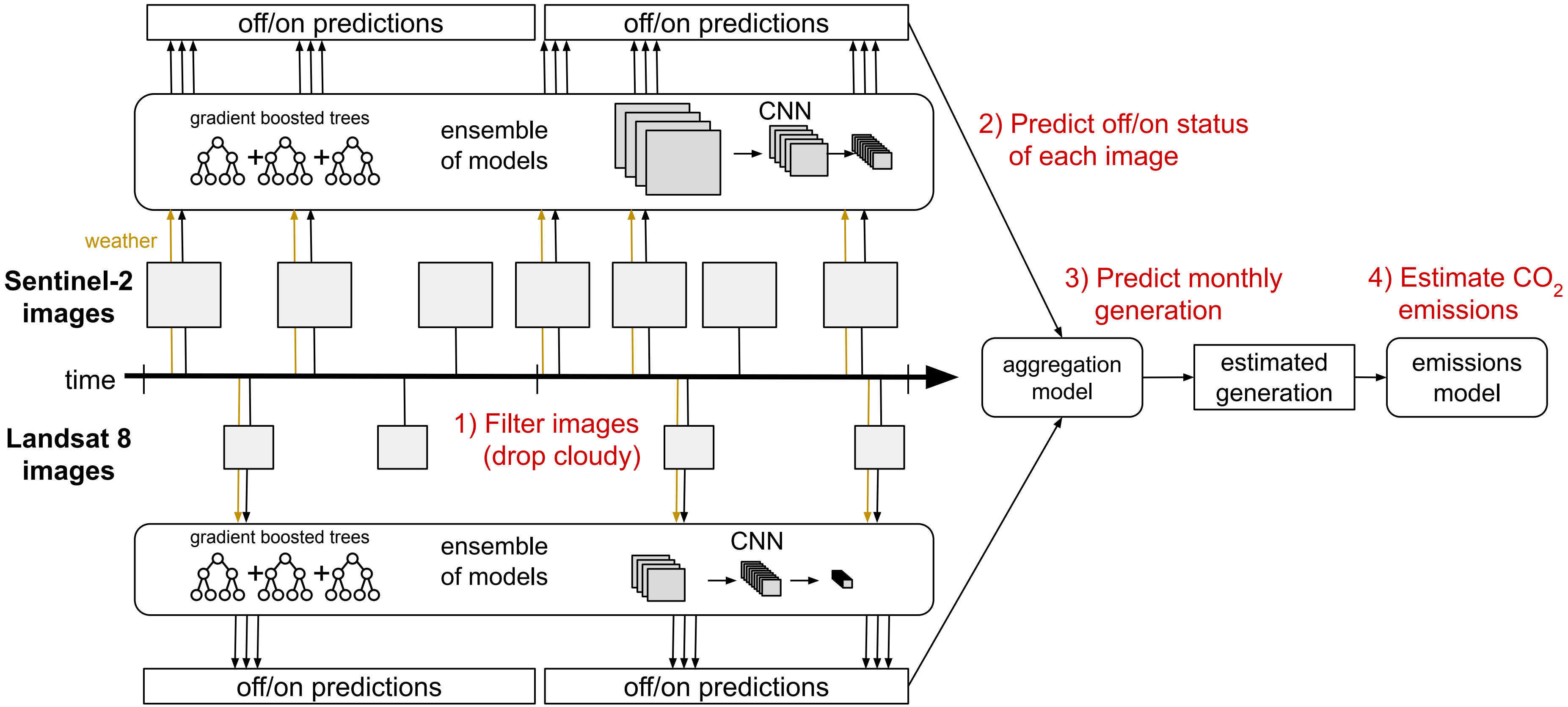
Model type	Sentinel-2 mAP	Landsat 8 mAP
Mechanical/natural draft		
ROI Gradient Boosted Trees	0.647	0.616
ROI+Patch Gradient Boosted Trees	0.789	0.713
ROI Convolutional Neural Network	0.681	0.651
Patch Convolutional Neural Network	**0.813**	**0.756**
Once-through		
ROI Gradient Boosted Trees	0.616	**0.627**
ROI+Patch Gradient Boosted Trees	**0.626**	0.606
ROI Convolutional Neural Network	0.612	0.598
Patch Convolutional Neural Network	0.623	0.566

Failure cases:

Plume not always visible when temp high or humidity low

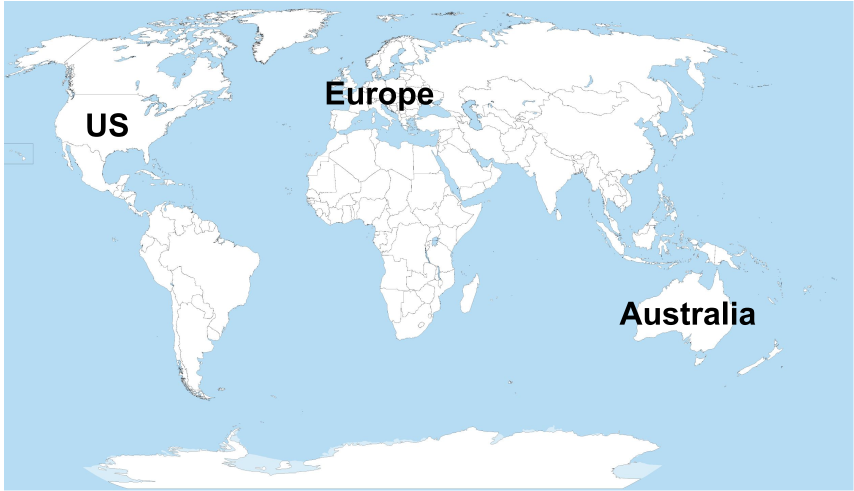
Smoke plume only can be difficult to see

Next step: aggregate into monthly emissions estimates



Validating our global model will be a challenge

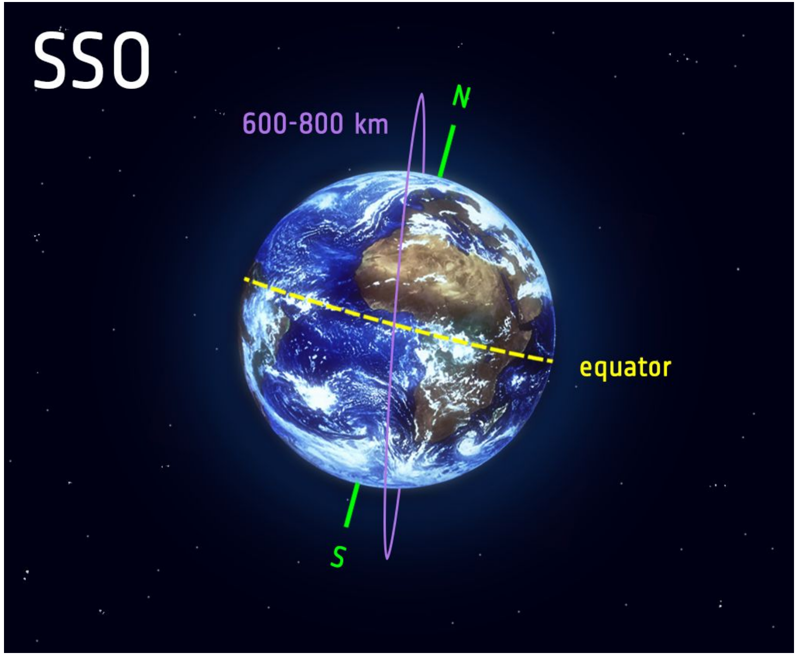
1) Training data is limited and may not be representative of plants globally



Granular emissions data: US

Granular generation data: US, Europe, Australia

2) Observation times are limited by satellite orbits



https://www.esa.int/ESA_Multimedia/Images/2020/03/Polar_and_Sun-synchronous_orbit

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