Tracking Climate Change Causes and Impacts using Satellite Imagery and Artificial Intelligence

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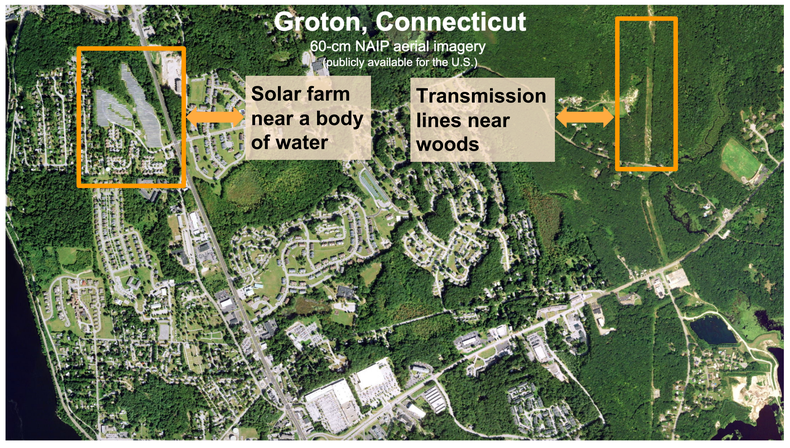
Climate+

1 Motivation & Research Goal

With climate change bringing significant impacts to society, it is important to inform climate change mitigation and adaptation strategies which requires a wide range of data. However, existing data are not always geographically complete or sufficiently up-to-date.

Our overarching mission is to enable global, automated assessment of energy infrastructure to develop pathways to sustainably address energy needs and climate impacts. To do this, our goal is to develop a technique that can take in text queries, and identify corresponding climate-relevant objects in remotely-sensed data. This will allow researchers to quickly collect valuable information from remotely-sensed data such as location and characteristics of key infrastructure and the impacts on natural resources.



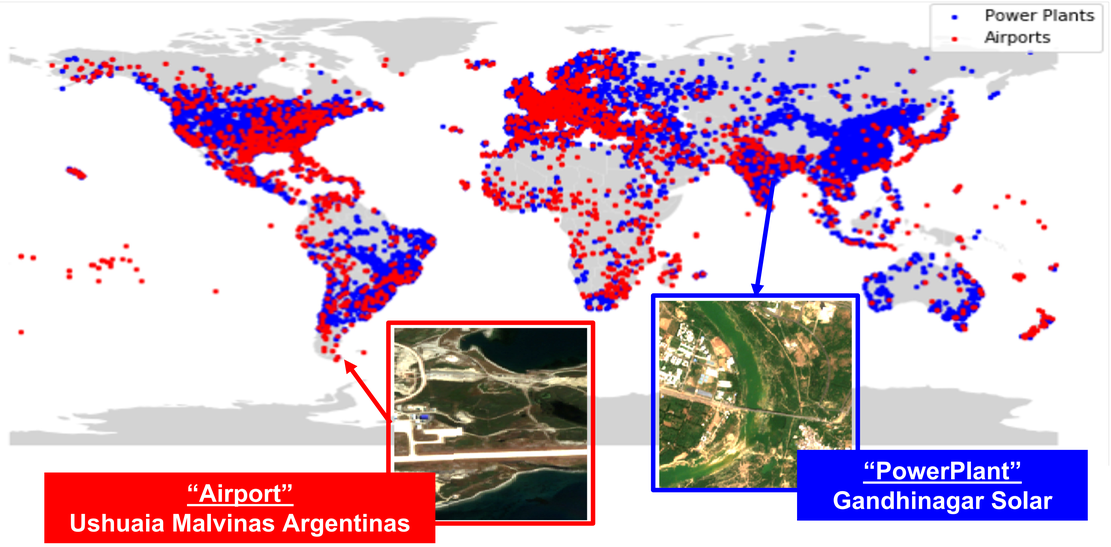
2 Challenges

- Training a new artificial intelligence model from scratch is costly and time-consuming, and requires a lot of labeled data
- Large quantities of high quality satellite imagery data with associated labels (e.g., “airport”) are expensive to collect and curate
- Existing state-of-the-art pre-trained artificial intelligence image recognition models are usually trained on data that does not adapt well to the unique characteristics of satellite imagery in the remote sensing domain

Remotely sensed data may vary significantly based on geography, sensor, and atmospheric conditions.

The images here are from the DeepGlobe and INRIA building segmentation datasets

3 Create remote sensing image-text pairs for model training



This example shows the coverage of two sets of text-image pairs in our tailored data corpus from Airports and Power Plants across the world. Each such pair has both a text label and an associated Sentinel-2 satellite image.

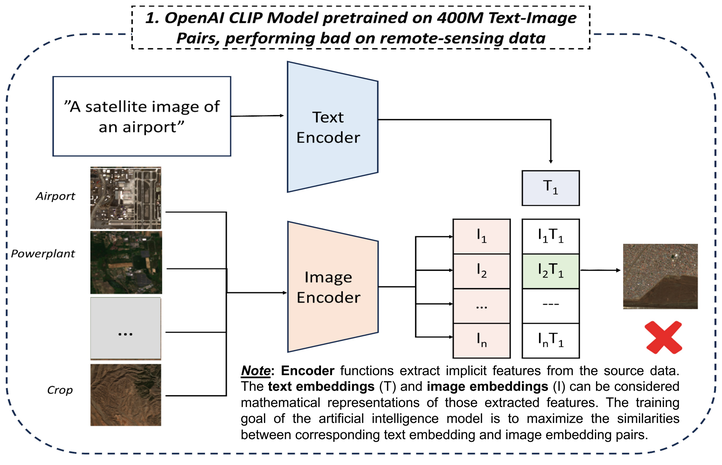
We compiled **11 million text-image pairs** to enhance the artificial intelligence model training process.

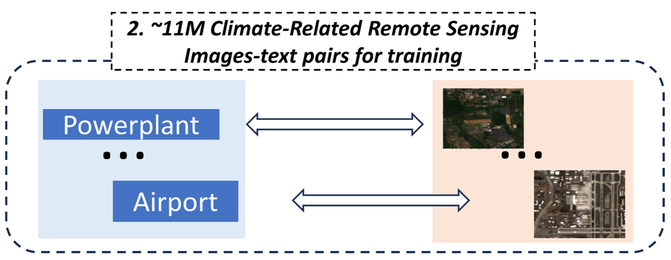
Text label categories within these images include climate-related features such as:

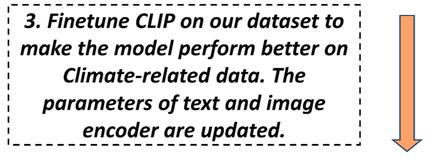
- Airports
- Power Plants
- Ports
- Offshore Installations
- Wind Turbines
- Coal and Metal Mining
- Glaciers
- Roads
- Crops

Images are previously collected Sentinel-2 satellite images and demonstrate global coverage of select climatic features.

4 Create a bidirectional text-to-image search tool for climate inquiries on satellite imagery

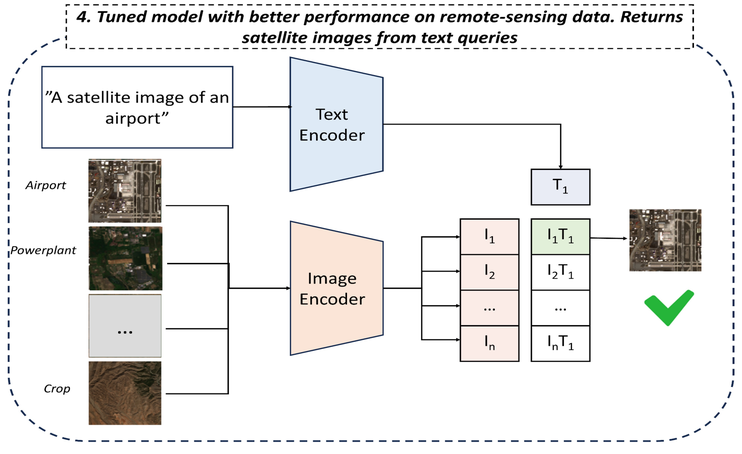






OpenAI published the CLIP model [1] in 2021, enabling bidirectional text-image mapping in a self-supervised manner (e.g., the model can extract implicit information from unlabeled data). CLIP was designed to enable high-quality text-image pairings without incurring the high cost of training a new artificial intelligence model from scratch. However, CLIP tends to perform poorly on remote-sensing datasets.

We instead tailor the pre-trained CLIP model and **finetune** it using our 11 million text-image pairs to learn meaningful domain-specific information from our own remote sensing datasets. This leads to a tailored AI model that can more accurately identify satellite imagery associated with a given text prompt to enable faster retrieval of key climate change related information for policy and other decision makers.



[1] CLIP: Connecting text and images