Hertie School

Tutorial for Sentinel-1 Flood Analysis: Transfer Learning and Embedding Applications

Deep Learning | Dec 2025

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Agenda

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2. Policy implications
3. Transfer learning for flood monitoring
4. Our tutorial | Data & methodology
5. Sentinel-1 Radar
6. Our tutorial | Overview

What is transfer learning?

Traditionally, machine learning requires the application of learned parameters from a source into a target task.

The problem

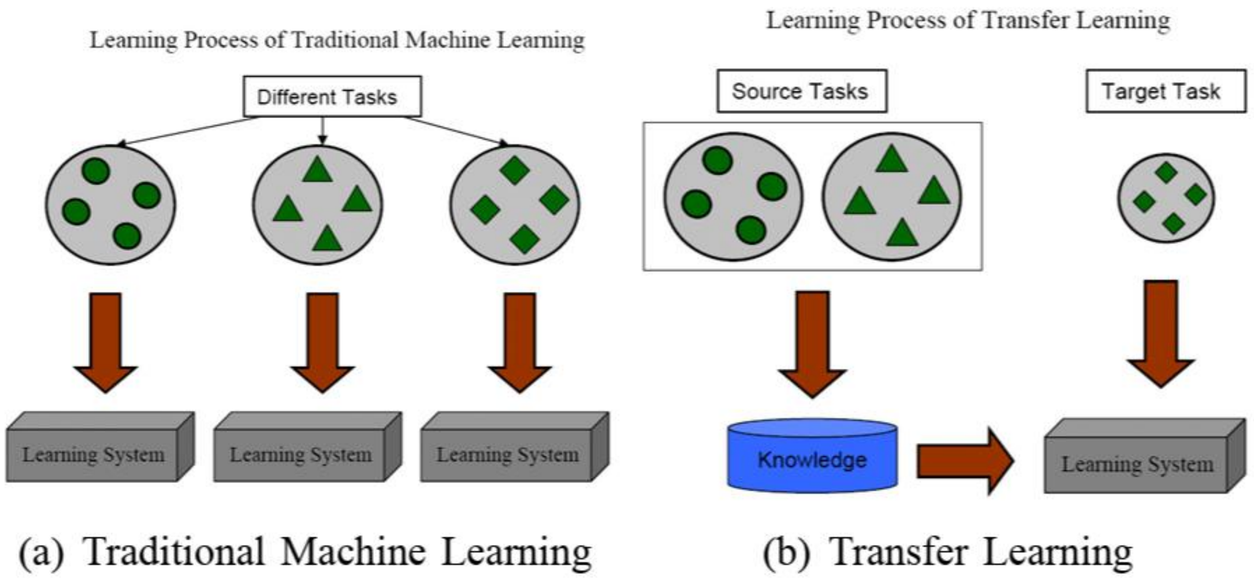
- Sometimes a model cannot generalize well in the context of a new task, or a new data distribution
- It can be expensive or even impossible to re-collect data and re-train a model

How do we reduce the need and effort to re-collect the training data?

Transfer learning!

What is transfer learning?

- In transfer learning, a model developed for one task can be **reused or adapted for another target task**
- The initial model has learned useful patterns and holds knowledge that can be fine-tuned or repurposed to a different problem
- Transfer learning is helpful in case of **limited labeled data**, or **when re-training is too expensive**



Pan, S. J. & Yang, Q. A survey on transfer learning, *IEEE Trans. Knowl. Data Eng.* **22**, 1345 (2010).

What is transfer learning?

Different scenarios of transfer learning

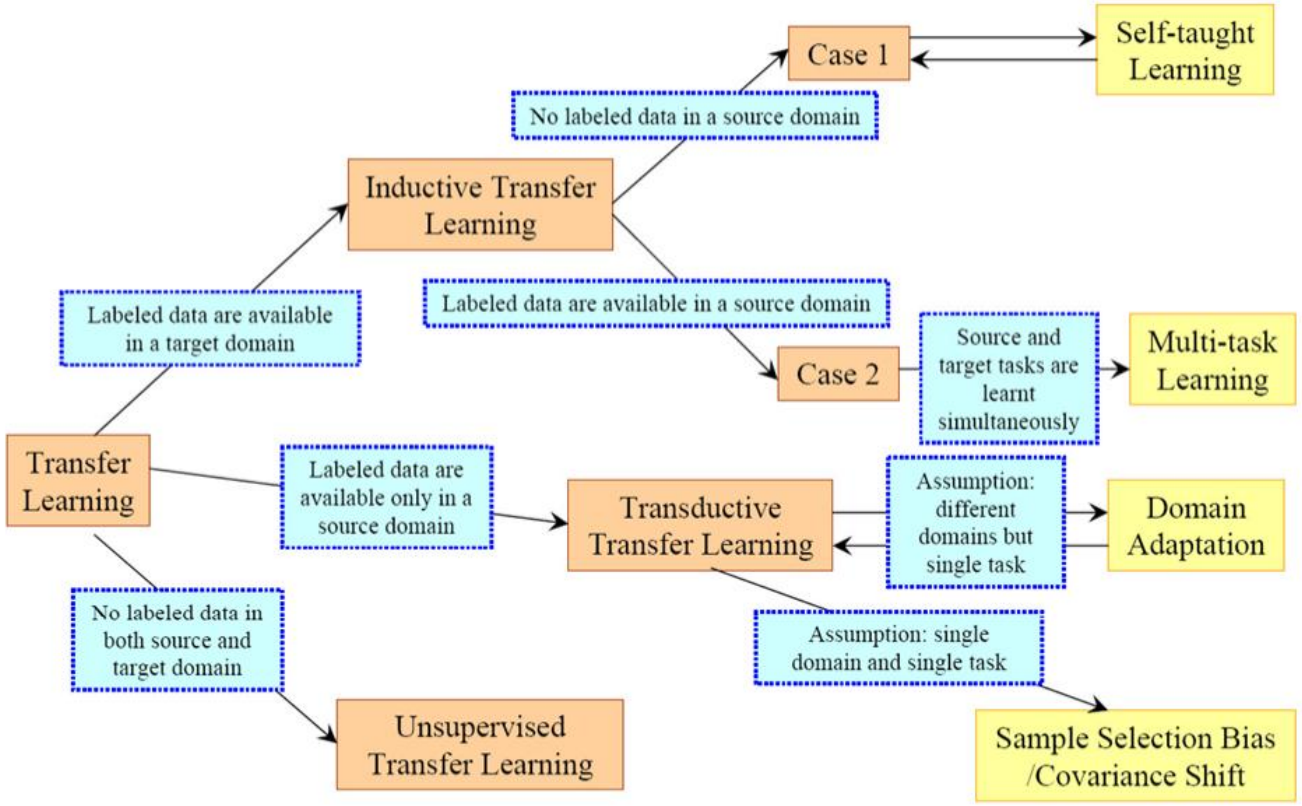


Fig. 2. An Overview of Different Settings of Transfer

Pan, S. J. & Yang, Q. A survey on transfer learning, *IEEE Trans. Knowl. Data Eng.* **22**, 1345 (2010).

What is transfer learning?

The **benefits** of transfer learning:

- **Requires less data**, once the pre-trained models already learned fundamental patterns
- Faster fine-tuning
- **Lower computational cost** as the training stage requirements are no longer an issue
- Enables tasks that would otherwise not be possible (e.g.: medical image classifiers, prediction of energy demand)
- Can lead to better accuracy and generalization!

X

The **challenges** of transfer learning:

- **Negative transfer**, when the source and target domains are not significantly similar, transferring may hinder the performance in the target
- If the target dataset is small, fine-tuning a large model may cause overfitting
- Catastrophic forgetting when fine-tuning, eroding previously knowledge
- Determining what to transfer/reuse
- **Data privacy issues** with repurposing the training data from the pre-trained model

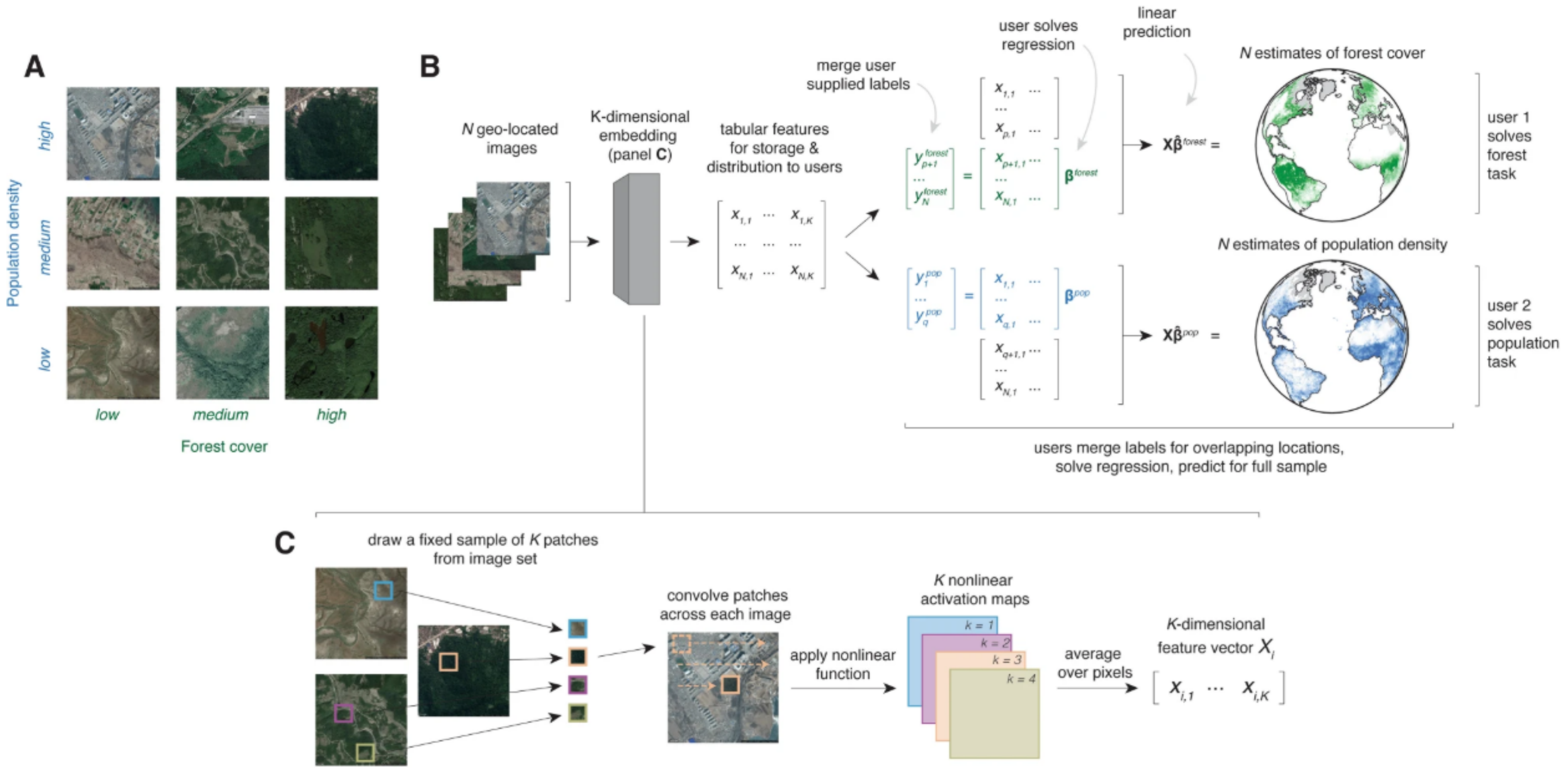
Public policy implications

- Complex global and policy issues often require the inclusion of several levels and layers of reliable large-scale data
- Often times traditional machine learning models fail due to **high complexity** of the samples, **lack of data**, or even the **high cost** of acquiring such data or train the models
- Transfer learning allows for scalability, cost-effectiveness and faster responsiveness to policy needs
- Policy makers must also take into account several regulations such as the EU AI Act, under which complex models can be used for high-risk tasks and therefore must comply to different sets of requirements
- In essential sectors such as healthcare and energy, transfer learning has been used to predict decarbonization efforts and energy demand, as well as medical imaging, for example
- **In combination with satellite imagery**, transfer learning can be used to predict infrastructure needs and keep track of characteristics such as forest cover, population density, land use, and even poverty rates

Public policy implications

Example: **Fig. 1: A generalizable approach to combining satellite imagery with machine learning (SIML) without users handling images.**

From: [A generalizable and accessible approach to machine learning with global satellite imagery]



Rolf, E., Proctor, J., Carleton, T. *et al.* A generalizable and accessible approach to machine learning with global satellite imagery. *Nat Commun* **12**, 4392 (2021).

Transfer learning for flood monitoring

August 2025 floods in India.

- Flooding is one of the most damaging climate-related hazards today, capable of destroying infrastructure, reduce agricultural output, and threaten lives
- The UN Office for Disaster Risk Reduction points out **floods account for up to 35-40% of weather-related disaster occurences**, and
- Since 2000, **the number of recorded flood-related disasters has risen by 134%** compared with the two previous decades.

Transfer learning for flood monitoring

- Governments increasingly rely on satellite imagery to monitor floods, especially in regions lacking ground sensors
- Interpreting satellite radar data requires technical expertise and manual processing

Deep learning models can help analysts produce rapid, large-scale flood maps, supporting emergency response, disaster insurance, infrastructure planning, and climate adaptation strategies

August 2025 floods in India.

Our tutorial | Data & methodology

Small subset of the Sen1Floods11 dataset: a public, georeferenced benchmark for training flood-mapping models from satellite data

The dataset contains flood events across multiple countries and includes:

- Sentinel-1 SAR Imagery, which penetrates clouds and is perfect for flood detection
- Hand-labeled flood masks, where each pixel is annotated as:

1	=	water (flooded)
0	=	non-water
-1	=	no data/invalid

With transfer learning, we can train a pixel-level flood-segmentation model with fewer labeled images that would be required to train a model from scratch

Instead of learning all features from zero, we start from a pretrained CNN that already captures general image structure, accelerating learning and reducing data we need!!

Sentinel-1 Radar

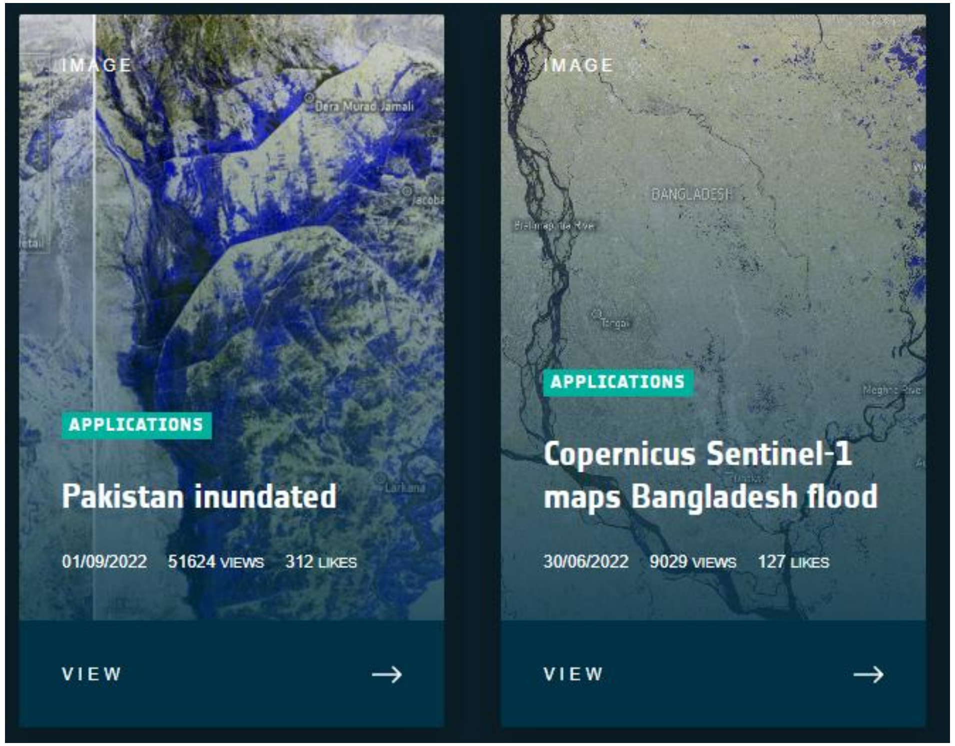
- Sentinel-1 Radar: a Synthetic Aperture Radar (SAR) mission that provides microwave imagery independent of daylight or weather conditions, making it particularly valuable for flood monitoring.
- SAR backscatter is sensitive to water, making it ideal for detecting floods even under cloud cover.
- Each Sentinel-1 image contains two polarization channels:

VV Polarization (Vertical Transmit, Vertical Receive)

- Measures backscatter where the transmitted and received microwaves are both vertically polarized
- Highly sensitive to surface roughness (soil, open water, built structures)
- Excellent for detecting open-water flood extents

VH Polarization (Vertical Transmit, Horizontal Receive)

- Measures microwaves transmitted vertically but received horizontally
- Sensitive to volume scattering, especially from vegetation, crop fields, and forest canopies
- Useful for detecting flooding beneath vegetation, which is often invisible in VV alone



Source: European Space Agengy.

Our tutorial | Overview

We are building a pre-trained **SAR flood detection model** using Sentinel-1 imagery that generalizes across regions and produces **portable feature embeddings** for downstream tasks such as flood classification and few-shot learning.

Architecture of the model

- U-Net with a ResNet34 encoder
- ImageNet → SAR transfer learning

Dataset

- 150 chips (512×512 pixel tiles of satellite imagery) from the Floods11 benchmark
- Regions: USA, India and Paraguay
- Two channels: VV & VH polarization

Two-stage transfer learning

1. Train decoder only (encoder frozen) → *3 epochs*
2. Fine-tune entire model (encoder unfrozen) → *10 epochs*

Results

- IoU: 0.62
- Accuracy: 95% on test set

Our tutorial | Overview

For the feature extraction pipeline, the fine-tuned encoder compresses **524,288 pixels** into **512-D embedding vector**, creating a representation of flood-relevant patterns

Each feature captures patterns like:

- Water darkness level
- Floodwater texture
- Linear structures (roads, levees)
- Smooth vs. rough backscatter
- Vegetation–water boundaries

Output

- Reusable **encoder weights**
- Use as a universal **SAR embedding generator** for any Sentinel-1 image
- No retraining required for downstream tasks

Our tutorial | Overview

Downstream use cases

1. **Binary flood classification**
Use embeddings or segmentation map to detect flood presence

2. **Similarity search**
Find historical flood events that resemble a new disaster

3. **Clustering**
Group floods by type (riverine, coastal, urban, shallow/deep patterns)

4. **Regional fine-tuning**
Adapt to a new region with only 20–30 local images

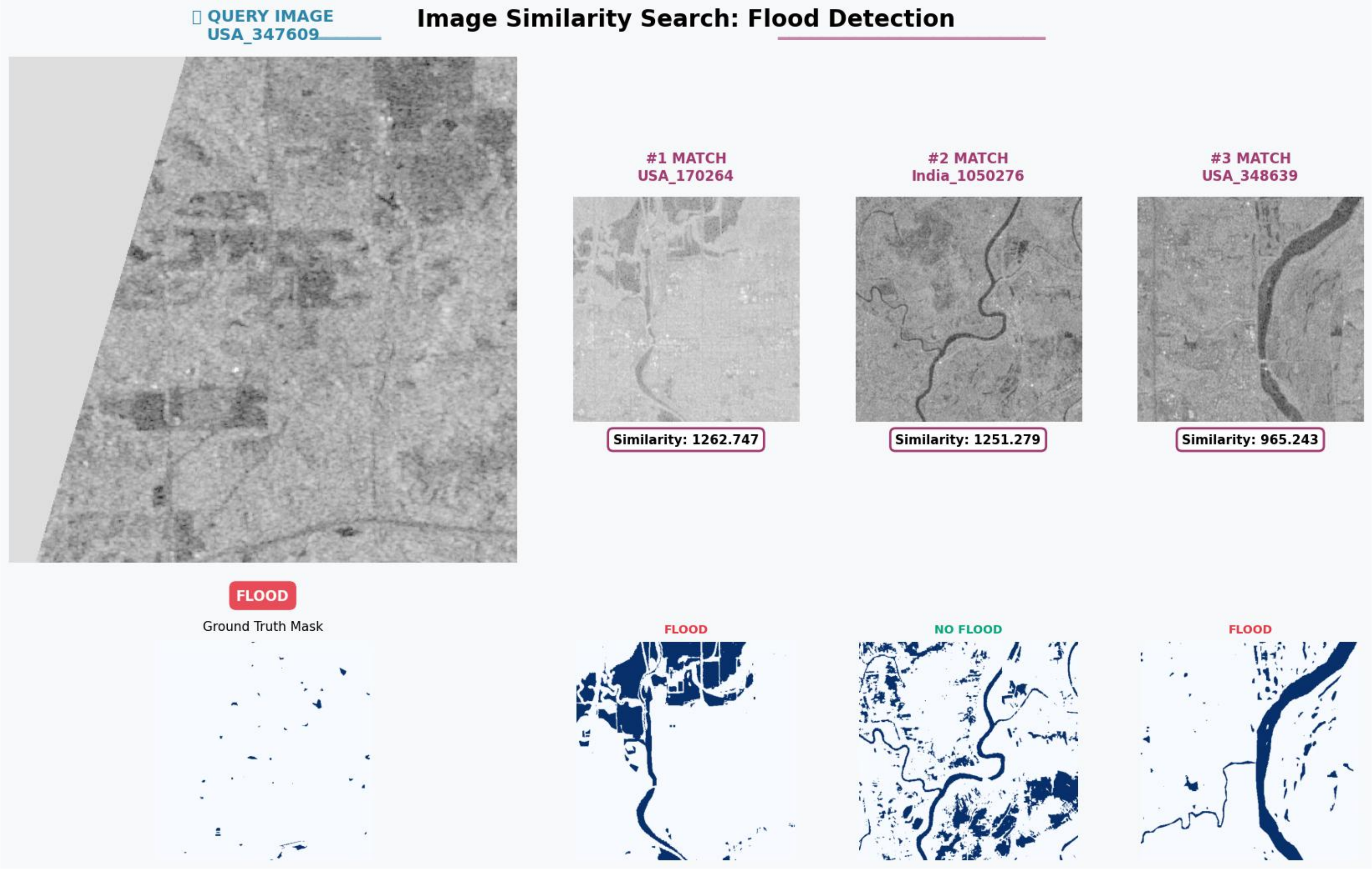
Key takeaway

The fine-tuned encoder serves as a reusable Sentinel-1 representation model: it enables downstream tasks without retraining**,** allows fast deployment, supports efficient fine-tuning, and versatile analysis workflows.

Similarity search for flood detection

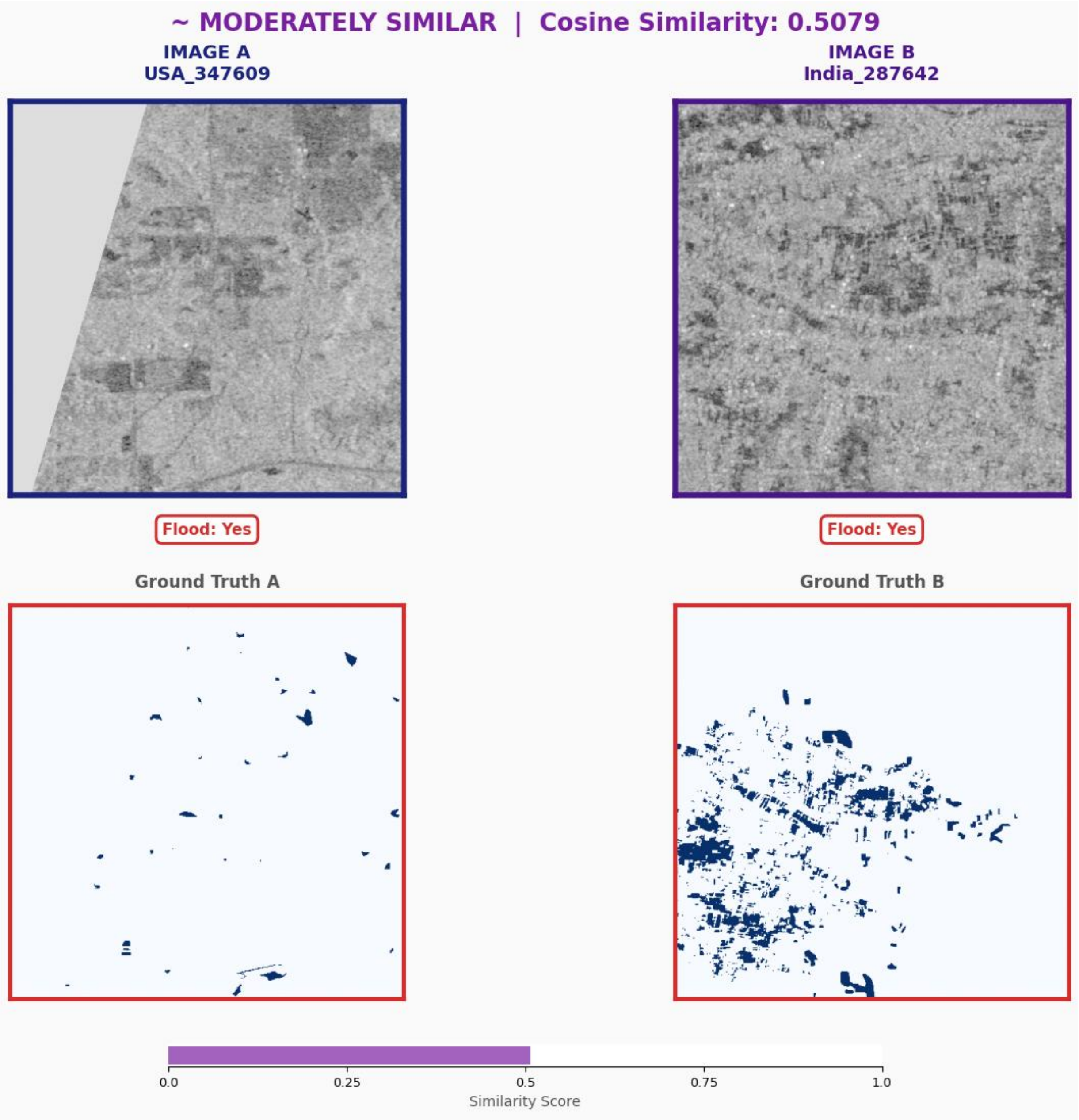
Embedding-based similarity search:

- The query SAR image (USA) is compared against all other chips using the 512-D embedding
- Ground-truth masks below reveal whether the matched scenes contain flooding, showing how similarity search can support rapid disaster assessment



Cross-region similarity

- The two chips both contain flooding, so the model assigns a moderate similarity score.
- The similarity reflects **shared flood textures**, backscatter signatures, and water-land boundaries, even though the scenes come from different regions.
- This shows that the embedding space balances **generalization** (detecting similar flood patterns globally) with **local variation** (not confusing different regions as identical)



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Thank you!