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# Transformers in Remote Sensing

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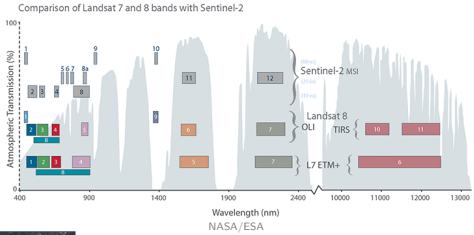
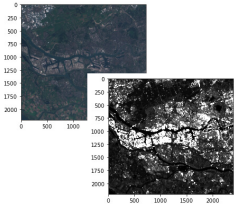
# Remote Sensing Data - Types

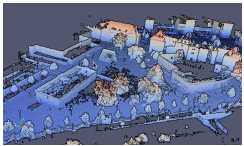
Most common remote sensing types are:

- Multi-/Hyper-spectral Optical:
  Passive scanning of reflected sunlight
- Synthetic Aperture Radar (SAR):
  Active emission of radar and detection of backscattered energy and polarizations
- Light Detection and Ranging (LiDAR):
  Active emission of laser and detection of backscattered energy



NASA/ESA

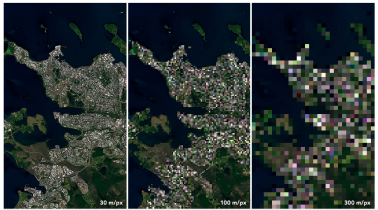

Optical (true color) and SAR observations of Aol Rotterdam


Bastian Steder, University of Freiburg, Dept. of Computer Science, Creative Commons Attribution License 3.0

# Remote Sensing Data - Resolution

Resolutions can be categorized:

- Low Resolution (LR): $>$ 30 m/pixel
- Medium Resolution (MR): 5-30 m/pixel
- High Resolution (HR): 1-5 m/pixel
- Very High Resolution (VHR): $<$ 1 m/pixel




*Landsat 8 image of Reykjavik, Iceland, acquired July 7, 2019, illustrating the difference in pixel resolution. Credit: NASA Earth Observatory.*

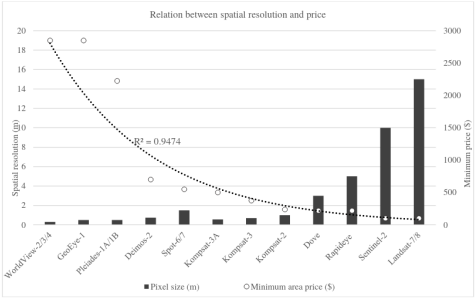



**Figure 1 Comparison between price and spatial resolution**

Based on the minimum price area and the estimate precision agriculture advantages (30$ ha$^{-1}$), a calculation of the break-even point for all the sensors was performed.

Image from Sozzi et al., 2018: Benchmark of Satellites Image Services for Precision Agricultural use

# Change Detection

- First mentioned 1964 by Shepard: "A **change detector device** is needed which will automatically correlate the overlapping area and indicate all the changes."
- Many menthods for Change Detection (CD) were created since then:
  - Difference (optical) or ratio (SAR)
  - Decision trees
  - Change Vector Analysis (CVS)
  - Slow Feature Analysis (SFA)
  - Principal Component Analysis (PCA) and clustering
  - ...
  - **Deep Neural Networks (DNNs)**

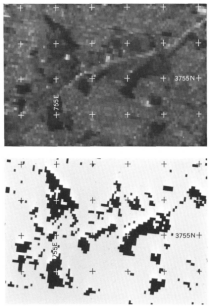



FIGURE 3.—Digital analysis of temporal overlay of Landsat band-5 data. Upper, ratioed data (band 5, 1972, divided by band 5, 1974); Lower, land-use-change theme extracted from ratioed data. Approximate location of UTM 1.0-km tick marks (zone 16) indicates scale and direction.

Image from Todd 1977: Urban and Regional Land Use Change Detected by using Landsat Data

# What to Detect?

Detecting a specific type of change is hard:

- Buildings, Roads or infrastructure
- Mobile objects (cars, trucks, containers)
- Vegetation or phenology
- Trees and forests
- Water bodies

What about:

- Seasonal changes?
- Irradiance/lighting changes (shadows)?
- Atmospheric problems (clouds, haze, fog)?

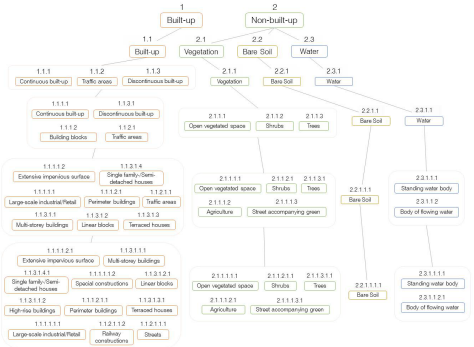
Figure 8. Examples of change detection in remote sensing images: left – input image A, middle – input image B, right – synthesized difference map

Image from Lebedev et al. 2018
(Season-varying CD Dataset)

# Detecting Urban Changes

What is actually *urban*?

- Let's alias built-up as urban
- Many different built-up sub-types
- Any change involves a transition from/to any type to/from built-up
  **Note:** This also involves from and to build-up!




Urban Structure Type from Lehner et al. 2019

# The Current DNN Methods

There are many methods but the current DNN-based ones are dominated by:

- Siamese networks: Two observations at two different times
- Curated VHR data, mostly RGB (only three spectral bands)

Fusion for Change Detection (CD):

- Image Level Fusion/Early Fusion
- Feature Level Fusion/Late Fusion
- Multi-scale Feature Fusion (Feature Pyramid, UNet, . . . )

Attention:

- Channel attention
- Spatial attention
- Self-Attention

# The Current DNN Methods - cont'd

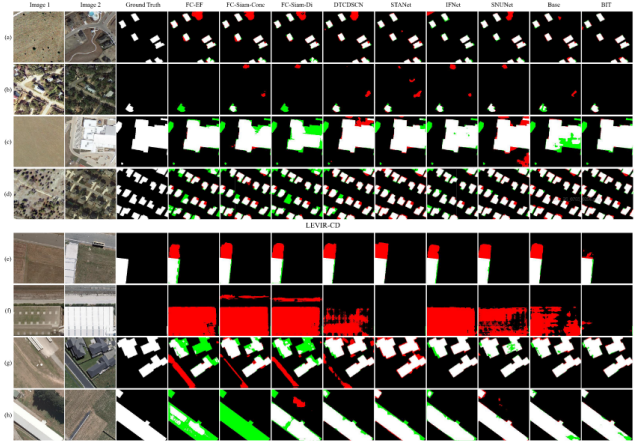



Image from Chen et al. 2022

# Bitemporal Image Transformer (BIT)

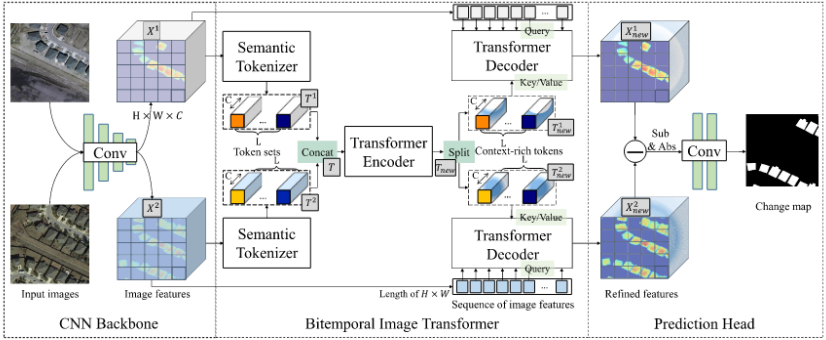



Fig. 2. Illustration of our BIT-based model. Our semantic tokenizer pools the image features extracted by a CNN backbone to a compact vocabulary set of tokens ($L \ll HW$). Then we feed the concatenated bitemporal tokens to the TE to relate concepts in token-based space-time. The resulting context-rich tokens for each temporal image are projected back to the pixel-space to refine the original features via the TD. Finally, our prediction head produces the pixel-level predictions by feeding the computed FDIs to a shallow CNN.

Bitemporal Image Transformer (BIT) from Chen et al. 2022

# Bitemporal Image Transformer (BIT)

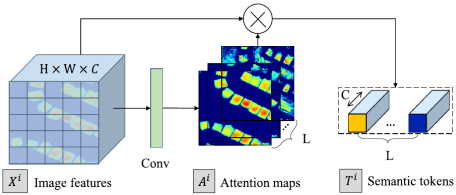



Fig. 3. Illustration of our semantic tokenizer.

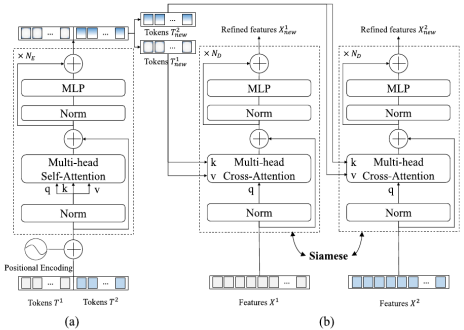
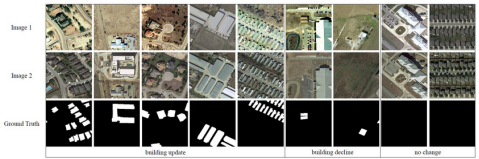



Fig. 4. Illustration of our (a) TE and (b) TD.

# Bitemporal Image Transformer (BIT) - cont'd

- Code is available on GitHub
- The LEVIR-CD dataset is used:
  - Originally 637 image pairs with $1,024 \times 1,024$ pixels
  - The 637 pairs are tiled into $256 \times 256$ patches
  - Images are RGB
  - Temporal span of 5-14 years
  - Contains ground truth labels (binary)
  - Only building changes are covered



# Demo Time

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