

# Investigation of an end-to-end neural architecture for image-based source term estimation

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SSPD  
Conference

# Problem definition

**Problem:** Increasing threat of hazardous releases:

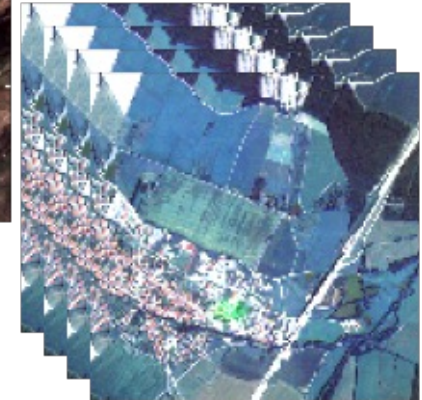
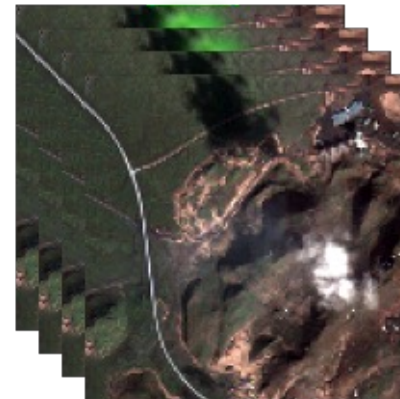
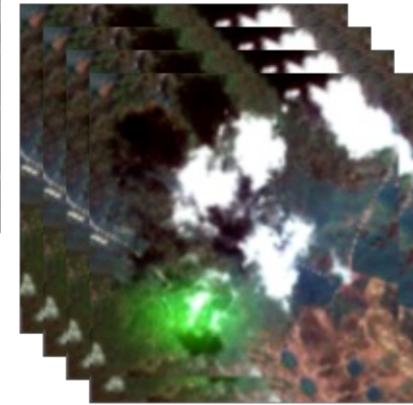
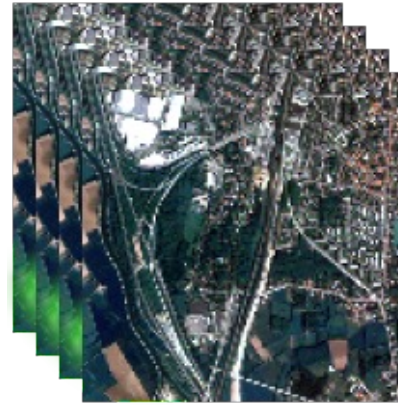
- Bhopal gas leak
- Fukushima nuclear accident
- Eyjafjallajökull volcanic eruption, ...

**Goal:** Determine

- location
- time of the release
- release mass
- meteorological data, ...

**Relevance:** Vital for:

- Monitoring environment
- Disaster management
- Legal compliance, ...



# Atmospheric dispersion simulation (ADS)

**Purpose:** Predict spread of contaminants for post-emergency assessment.

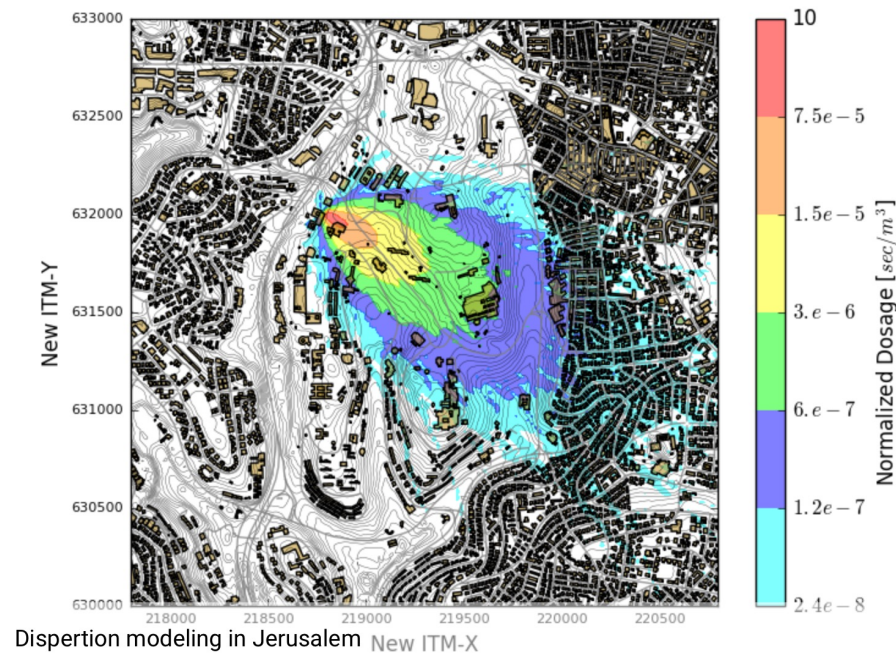
**Popular Model:** Gaussian Puff and Plume models (simple and efficient).

## Forecasting Inputs:

- Meteorological data (local/global sources).
- Release strength and location.

**Challenge:** Determining unknown strength, location, and timing from sensor data.

**Solution:** Source term estimation (STE) methods.



Credit: iibr.gov.il

# State of the art for STE

**Aim:** Optimal match between predicted and observed data.

## Bayesian Techniques:

- Produces estimates with confidence levels.
- Incorporates prior info through probability distributions.
- Typically computationally expensive.

## Optimization methods:

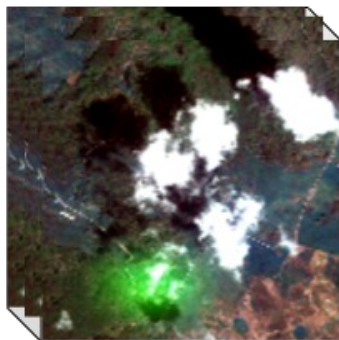
- Typically faster, less computationally demanding.
- Limited need for prior info, yet benefits from its availability.
- Generates only point estimates.

## Artificial neural networks (ANNs):

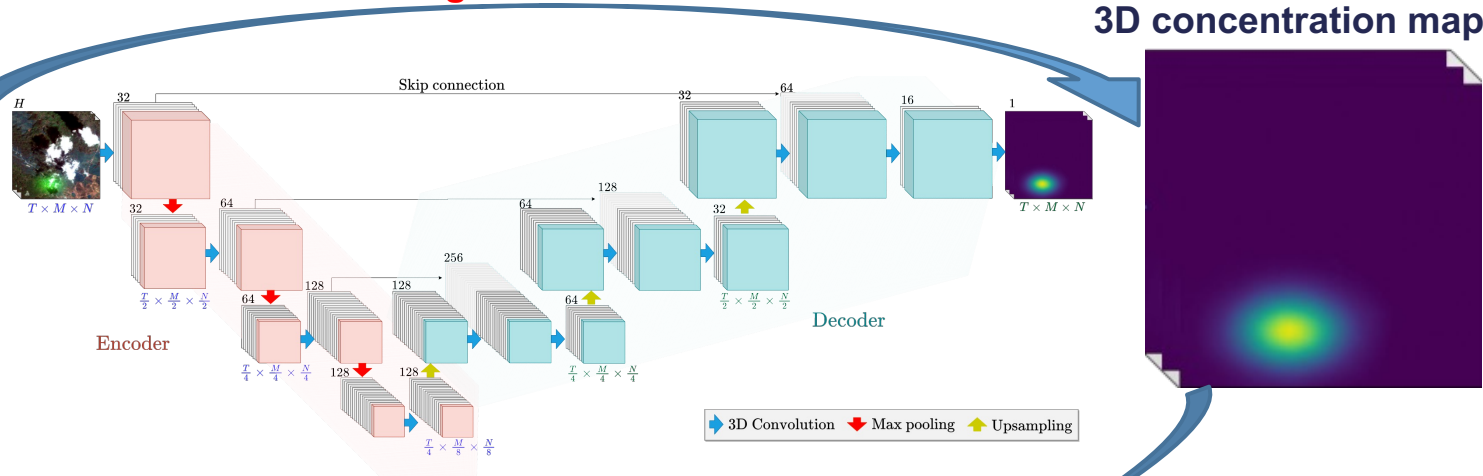
- Suitable for STE's nonlinearities.
- Enhanced by large training datasets and hardware accelerators.
- Existing ANNs focus on specific parameters.
- Often lack confidence intervals.

# Proposal

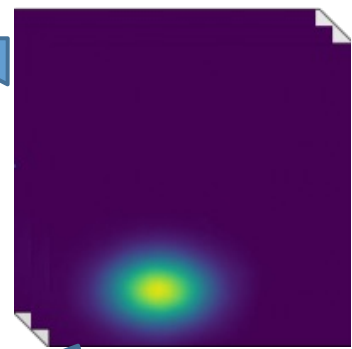
Time-series of hyperspectral satellite images



## First-stage ANN



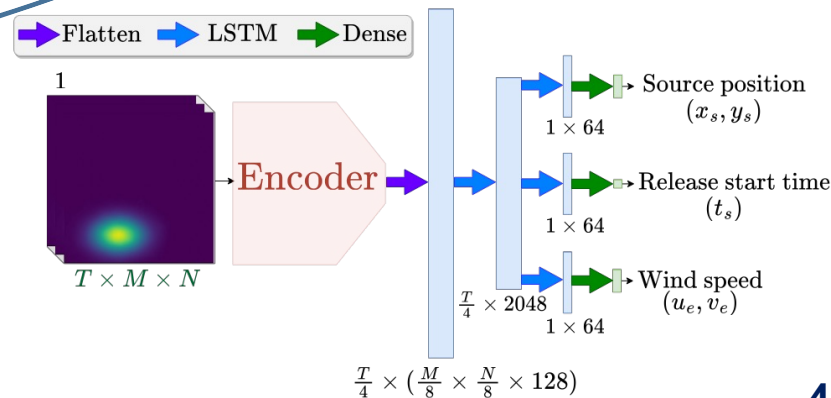
3D concentration map



## Second-stage ANN

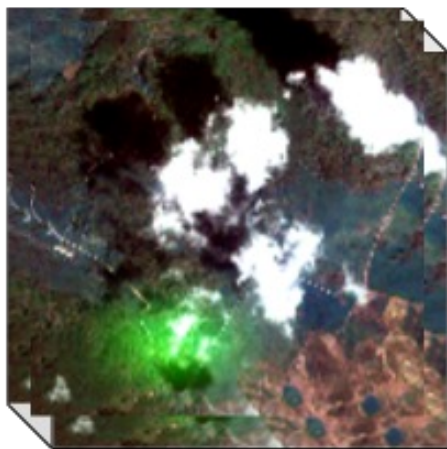
Source term parameters

- ❖ The starting time of the emission  $t_s$
- ❖ Position of the emission source  $(x_s, y_s)$
- ❖ The horizontal and vertical speeds  $(u_e, v_e)$



# First-stage ANN: Background removal

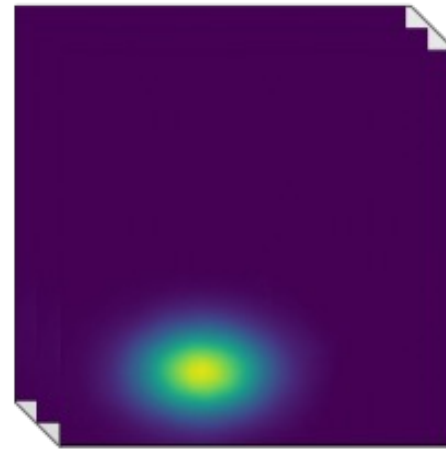
- ❖ Extracts the 3D concentration map from the time-series multi/hyperspectral satellite images.

 $H$  $T \times M \times N$ 

Background removal

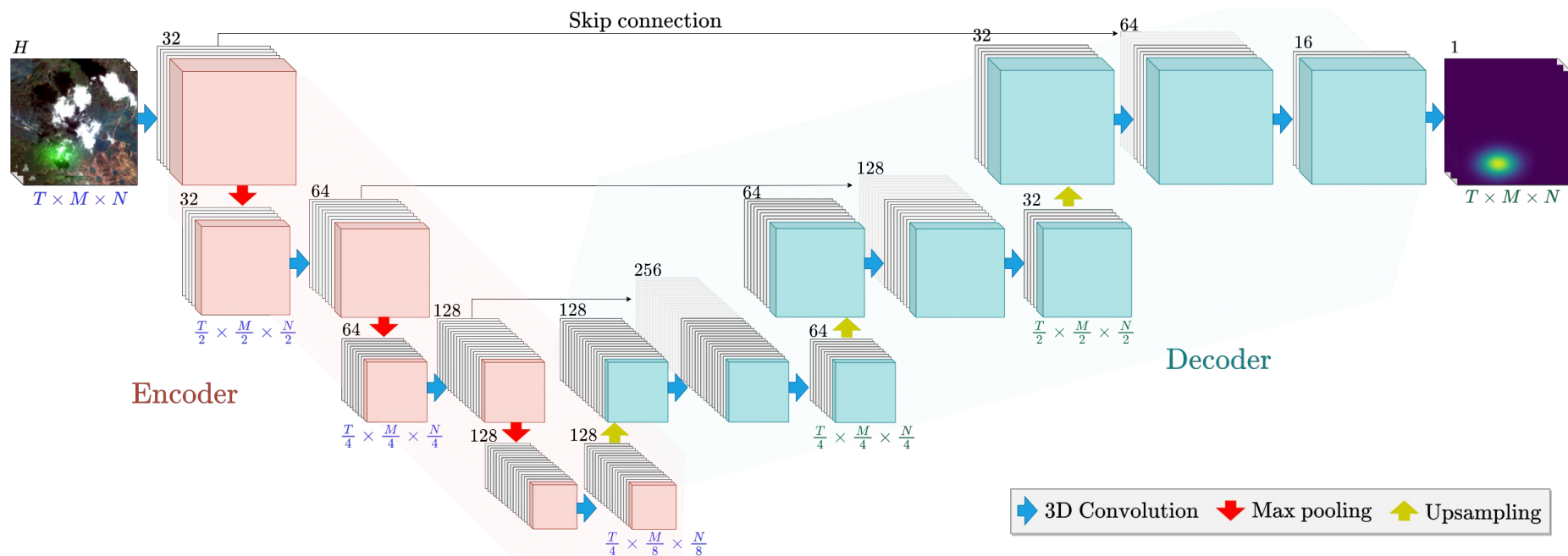


1

 $T \times M \times N$

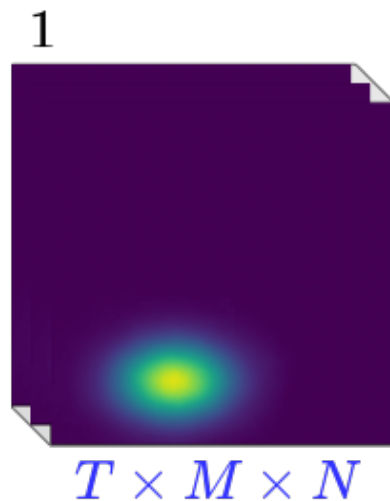
# First-stage ANN: Architecture

- ❖ **3D U-net architecture:** This design integrates both an encoder and a decoder, connected by skip connections.



## Second-stage ANN: STE

- ❖ Estimates the source term parameters from the extracted 3D concentration map.



Source term estimation



Source position  $(x_s, y_s)$

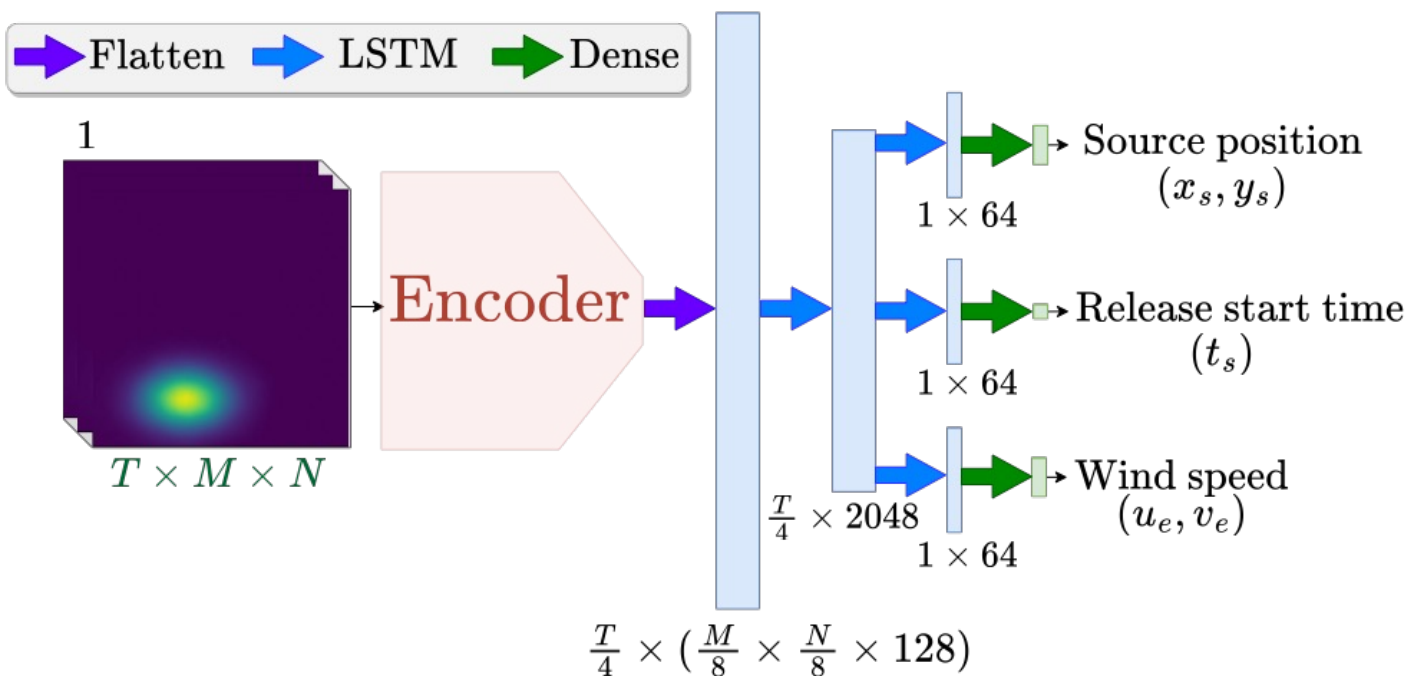
Release start time  $(t_s)$

Wind speeds  $(u_e, v_e)$



# Second-stage ANN: Architecture

- ❖ A deterministic ANN with an encoder-like structure for parameter estimation.



# Two-stage ANN Training

## Sequential Training:

1. Train first-stage ANN.
2. Train second-stage ANN with frozen first-stage.

## Training Details:

- Duration: 100 epochs.
- Optimizer: Adam.
- Learning Rate:  $10^{-3}$ .
- Batch Size: 30.

## Loss Function: Mean Squared Error (MSE).

- First branch: MSE between true and predicted concentration cloud.
- Second branch: MSE between true and predicted source term parameters.

# Simulations

## Data Collection:

- Source: Pleiades ESA archive.
- Total Images: 3200 (from 320 high-resolution satellite images).
- Image Dimensions: 128x128x3.

## Gas Release Simulation:

- Method: Gaussian puff model:

$$c(x, y, t) = \frac{q_s}{4\pi\sqrt{\sigma_x\sigma_y}} \exp \left[ -\frac{0.25}{(t - t_s)} \left( \frac{(x - x_s - u_e(t - t_s))^2}{\sigma_x} + \frac{(y - y_s - v_e(t - t_s))^2}{\sigma_y} \right) \right]$$

- Resultant Data: 4D cubes of 20x128x128x3 (20 time frames).

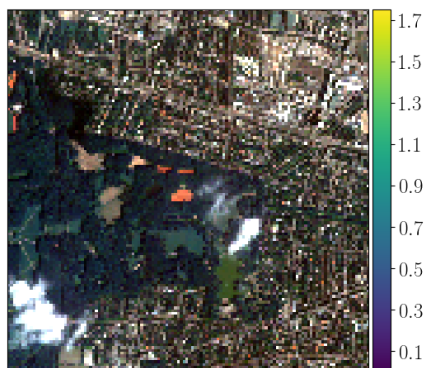
## Dataset Sizes:

- Training: 3000x20x128x128x3.
- Testing: 200x20x128x128x3.

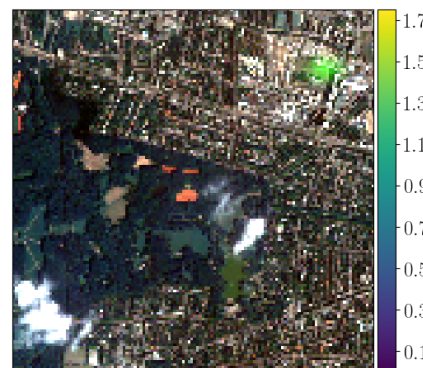
# First-stage ANN: Results

- ❖ Estimated concentration maps over time (second row) obtained from the corresponding satellite images (first row) using the 3D U-net. Displayed from left to right are the results for frames 1, 3, and 20.

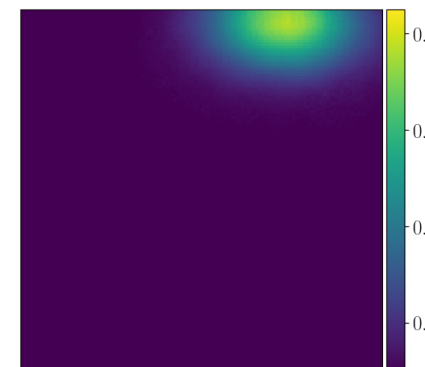
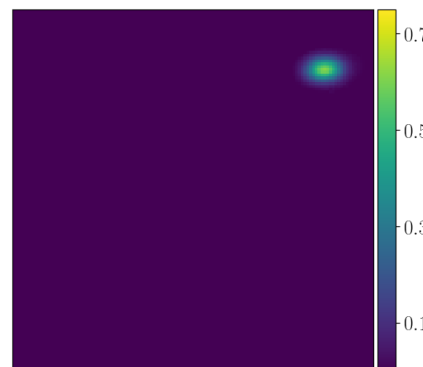
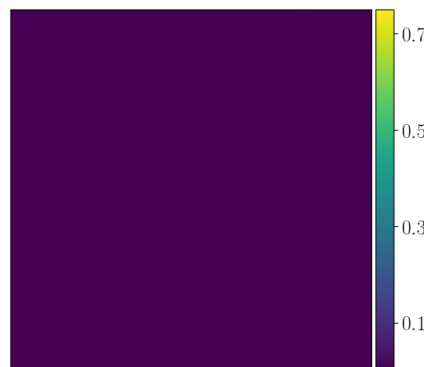
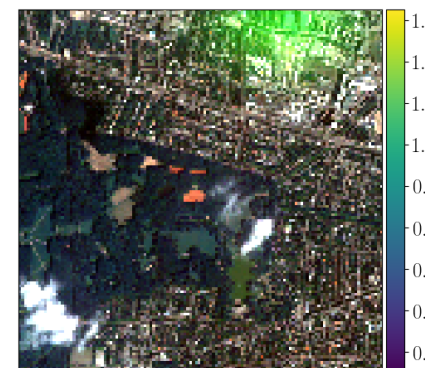
Frame 1



Frame 3



Frame 20



MSE =  $1 \times 10^{-6}$

## Second-stage ANN: Results

- ❖ Average MSE results between the predicted emission parameters, obtained using the second-stage ANN, and the true values for the testing dataset comprising 200 emission scenarios.

source term parameter	MSE
$x_s$	$1.16 \pm 2.04$ (pixels)
$y_s$	$0.99 \pm 1.67$ (pixels)
$t_s$	$0.09 \pm 0.15$ (frames)
$u_e$	$0.4 \pm 1.52$ (pixels)
$v_e$	$0.42 \pm 1.65$ (pixels)

# Conclusions & Future Work

## Findings:

- Introduced a two-stage ANN pipeline for STE using multispectral satellite imagery.
- Addressed STE's non-linearity.
- Offers rapid and precise hazard release estimation.

## Future Directions:

- Need for comparison with other STE methods.
- Conduct an uncertainty analysis.
- Refine architecture: Explore VAE integration.
- Enhance real-world applicability: Address irregular timings and faint cloud detection.
- Re-evaluate training: Consider end-to-end training or single network approach.

**Thank you for your attention!**