# Predicting Socio-economic Indicator Variations with Satellite Image Time Series and Transformer

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# Outline

# Context

We[a] want to produce world maps that report:

- Consumption expenditures,
- Income per household,
- Asset index,
- Wealth index,
- ...

*Chi et al. PNAS'2022 "Micro-Estimates for all low- and middle-income countries." http://3.15.84.96/brief/*

[a] Socio-economists, ecologists, remote sensing researchers, computer scientists, ...

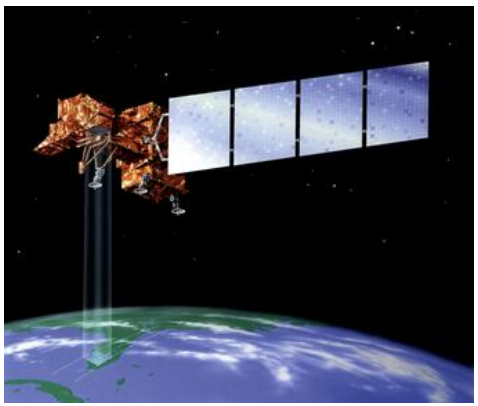
# Problem and Solution

## Problem:

Need to conduct surveys in many places and very often
→This is costly and time-consuming

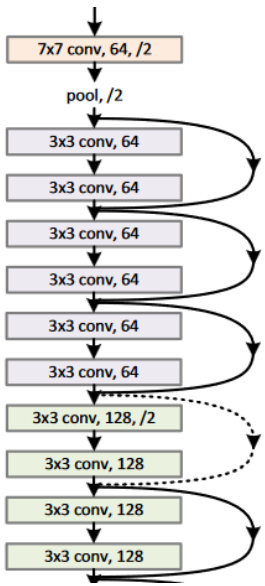
## Solution:

Use satellite images and deep learning.



*Landsat 7 Satellite*

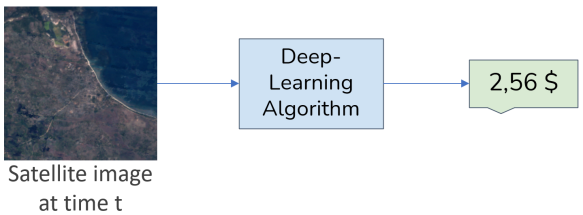
*Village in Tanzania*



# Outline

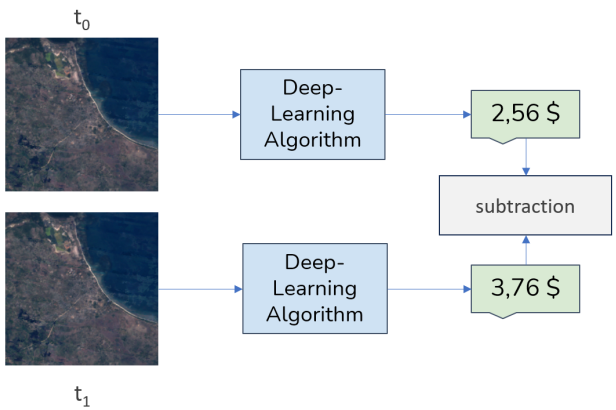
# State-Of-The-Art

## Prediction at a given date




[2, 4, 11, 12, 14, 15,...]

## But we are looking at a variation (i.e. $\approx$ a math difference)




Problem: The uncertainty of each prediction value (due to noises) leads to **uncertainty** on the result of the **subtraction** which is **higher than the variation range** [12, 22].

$\Rightarrow$ The subtraction must not be used (= uncertainty result).

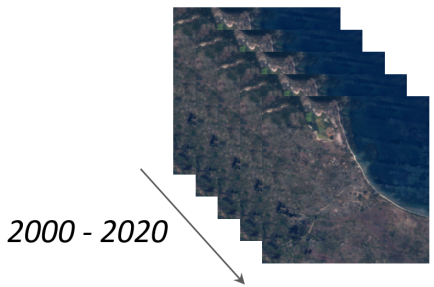
# One way to improve the confidence in the predicted variation

Integration of the temporal aspect:

- Yeh et al. [22] take as inputs 2 images (at start and end time) for their CNN.
- Our proposition:
  1. Use of a sequence of images,
  2. Use a transformer,
  3. Pretrained on a related pretext task.

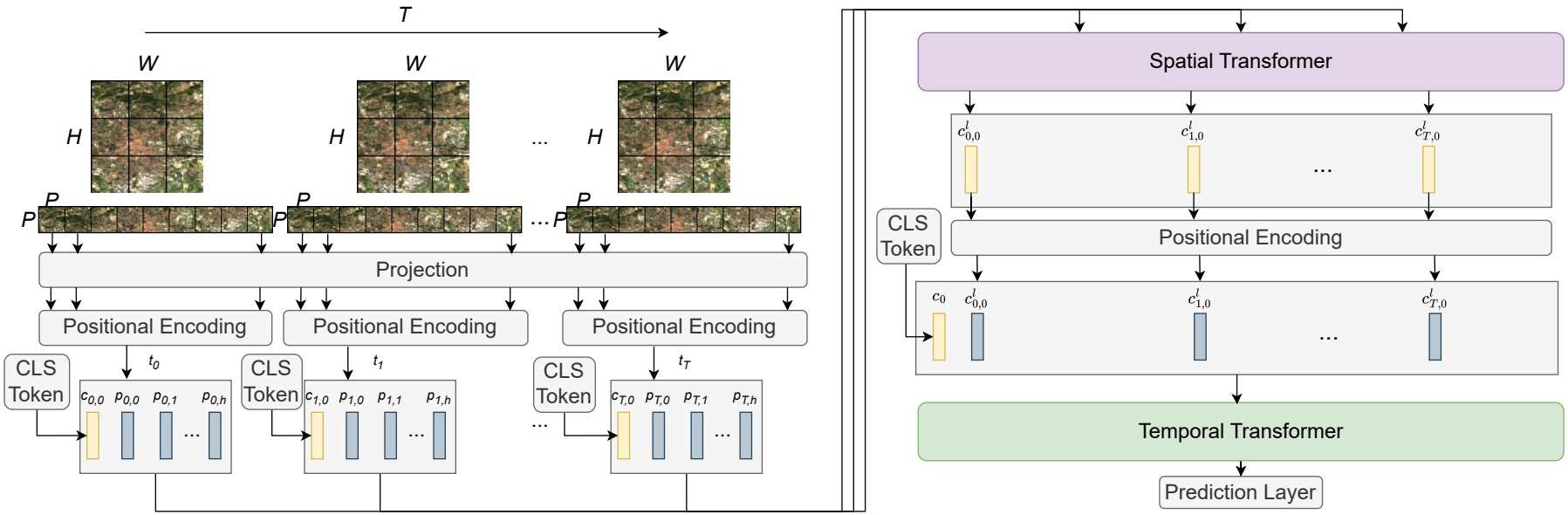
# Outline

# Ingredient 1: Use a Satellite Image Time Series (SITS)




- One year Landsat−7 median composite images,
- From 2000 to 2020,
- Resolution = 30 meters,
- Image size = 224×224 ($\approx$ 6.72 km$^2$),
- PRETRAIN = Subset of Africa and Middle East (9795 SITS),
- TRAIN = 1665 locations (i.e 1665 SITS)
  (Nigeria, Ethiopia, Tanzania, Uganda, and Malawi).

# Ingredient 2: Use a ViVit

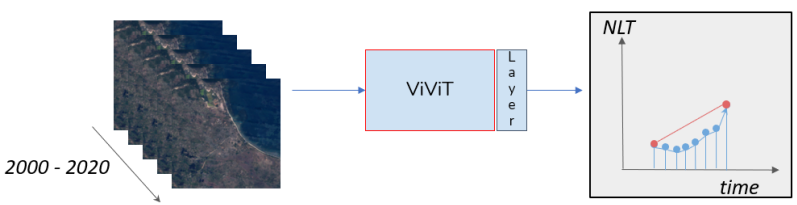



Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lucic, and Cordelia Schmid.
Vivit: A video vision transformer. ICCV'2021.

# Ingredient 3: (1) A pretraining

FIRST: A pretraining:

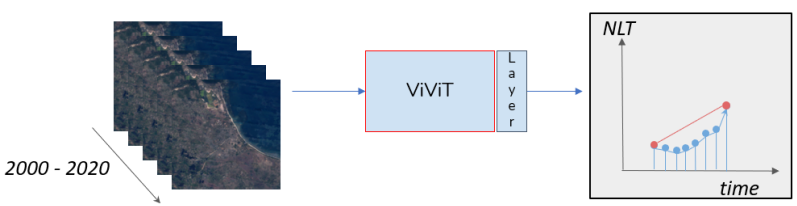
- On the whole 2000 - 2020 duration,
- To predict nighttime light time (NLT) **series**.
  *Note: NLT is correlated to our socio-economic indicator.*

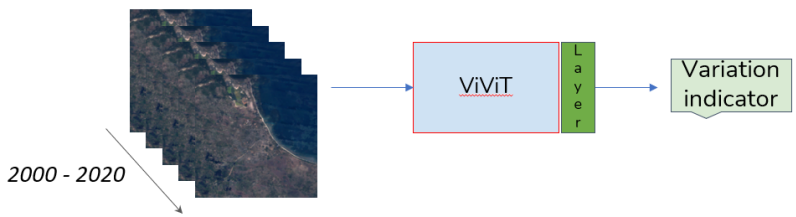


# Ingredient 3: (2) Finetuning

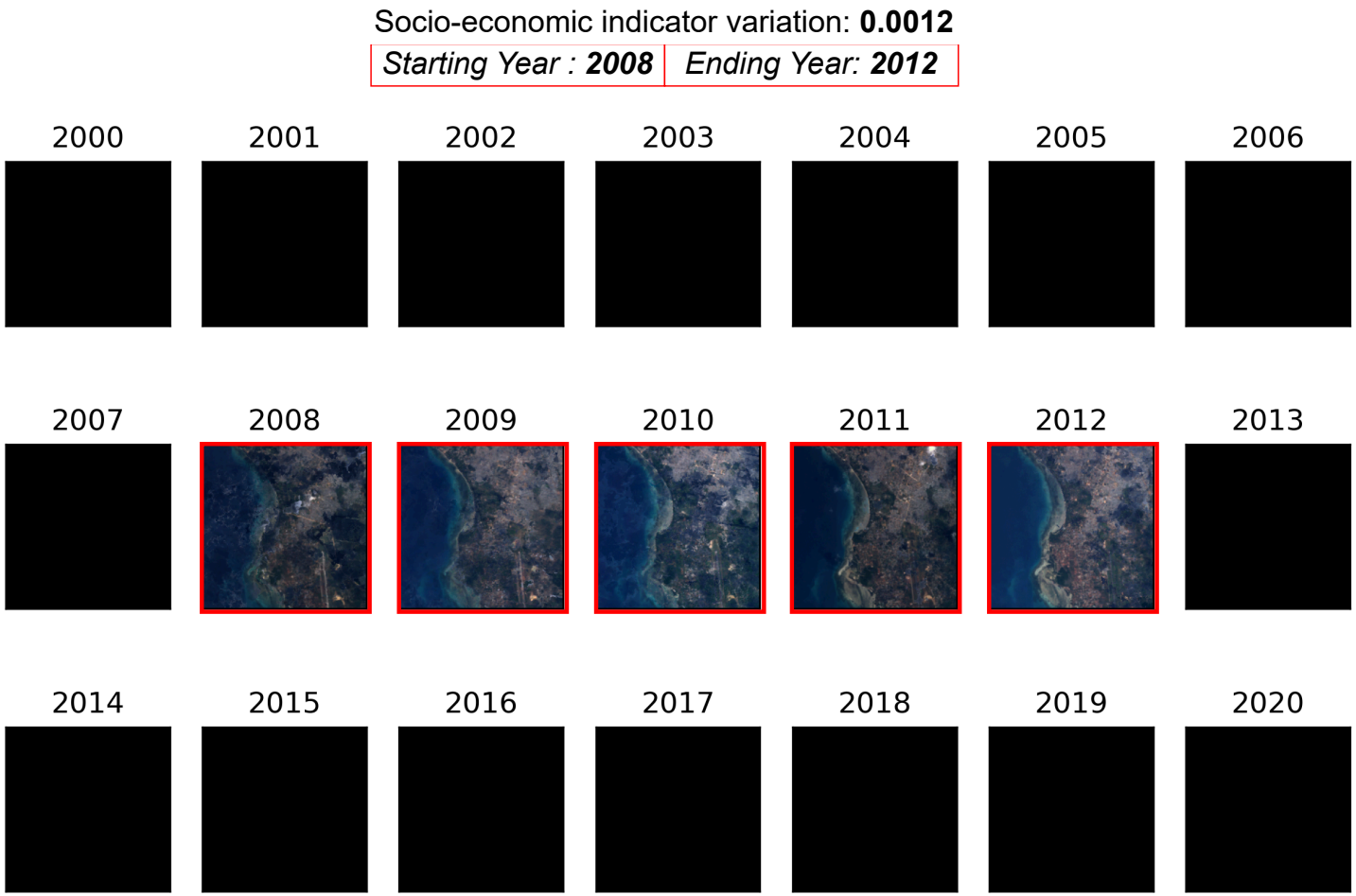
SECOND: A finetuning:

- Notion of start and end of a series,
- To predict the socio-economic **indicator** variation.



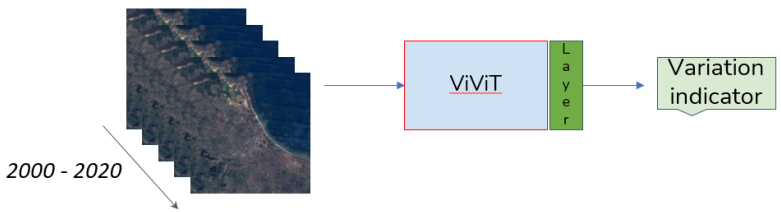



# Ingredient 3: Illustration of the masking



# Outline

# Experimental protocol




... prediction of the Socio-economic Indicator Variations.

- 1665 pairs of (SITS, variation indicator),
- 5 countries (Nigeria, Ethiopia, Tanzania, Uganda, and Malawi),
- 5-fold cross-validation (train on 4 folds and test on 1 fold), with no location overlap between folds,
- 250 epochs, MSE loss, Batch sizes=16, LR=5x$10^{-4}$, ...,
- ViVit 10 millions parameters, 4 Nvidia V100 GPU.

# Results:

| | $MAE \downarrow$ | $RMSE \downarrow$ | $r^2 \uparrow$ | $R^2 \uparrow$ |
|---|---|---|---|---|
| Yeh et al. (2 im) | $0.528^{\pm 0.019}$ | $0.687^{\pm 0.032}$ | $0.182^{\pm 0.054}$ | $0.122^{\pm 0.061}$ |
| Our appr. no pretrain | $0.482^{\pm 0.015}$ | $0.637^{\pm 0.020}$ | $0.263^{\pm 0.057}$ | $0.245^{\pm 0.054}$ |
| Our appr. with pretrain | $\underline{0.460}^{\pm 0.013}$ | $\underline{0.366}^{\pm 0.020}$ | $\underline{0.328}^{\pm 0.063}$ | $\underline{0.319}^{\pm 0.065}$ |

- MAE, RMSE, $r^2$, and $R^2$ are better,
- Note 1: Small performances due to small time range and small quantity of data ...
- Note 2: Evaluation on longer duration cannot be evaluated (no existing surveys),
- Note 3: Robustness to domain change have not been evaluated (insufficient number of surveys).

# Outline

# Conclusions

## Take away message:

- A new approach to predict socio-economic Indicator Variations,
- Consider spatio/temporal contexts
- Better than the State-Of-The-Art.

## Perspectives:

- Multi-sources and multi-modalities...