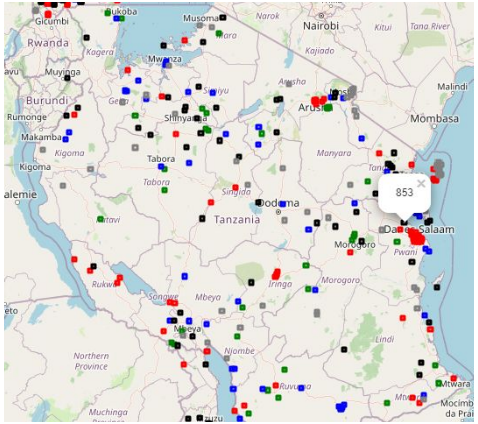
Comparing Spatial and Spatio-Temporal Paradigms to Estimate the Evolution of Socio-Economic Indicators from Satellite Images

Robin Jarry, ***LIRMM, Univ. Montpellier, CNRS, Montpellier, France***
Marc Chaumont, *LIRMM, Univ. Montpellier, CNRS, Montpellier, & Univ. Nîmes, France*
Laure Berti-Équille, *ESPACE-DEV, Univ. Montpellier, IRD, UA, UG, UR, Montpellier, France*
Gérard Subsol, *LIRMM, Univ. Montpellier, CNRS, Montpellier, France*

Estimating Poverty with Remote Sensing in Africa



G. Chi, H. Fang, S. Chatterjee, and J. E. Blumenstock. "Microestimates of wealth for all low-and-middle-income countries" (January 2022). PNAS,Vol 119, No 3.
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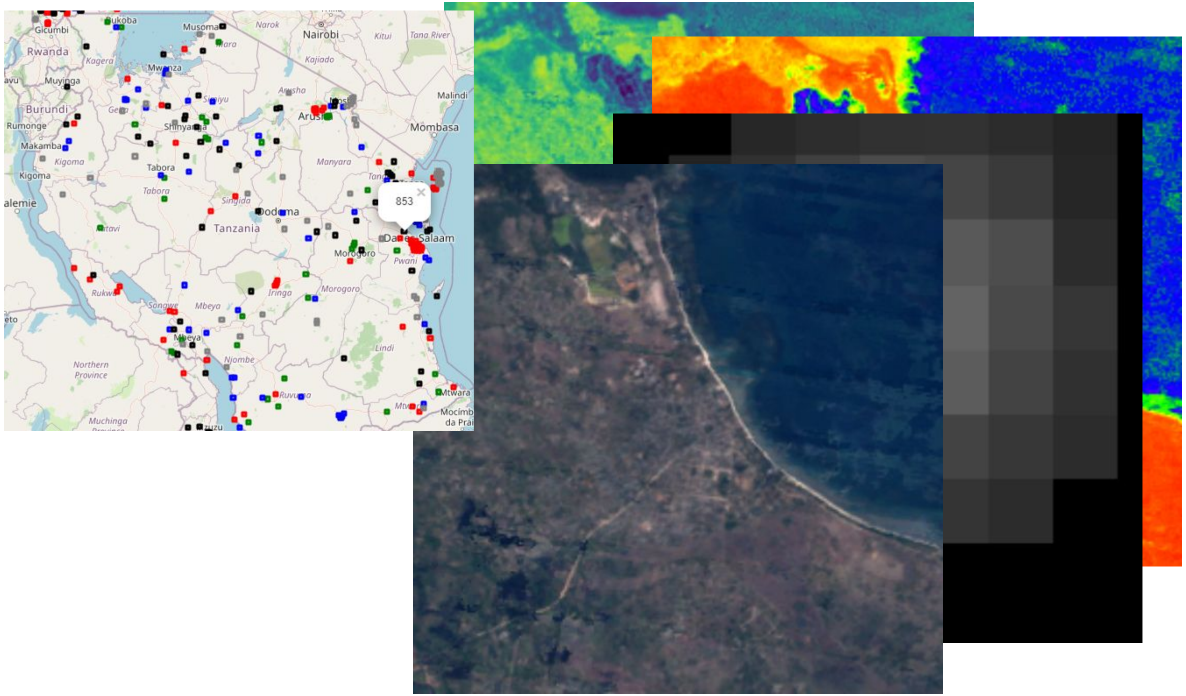
Estimating Poverty with Remote Sensing in Africa



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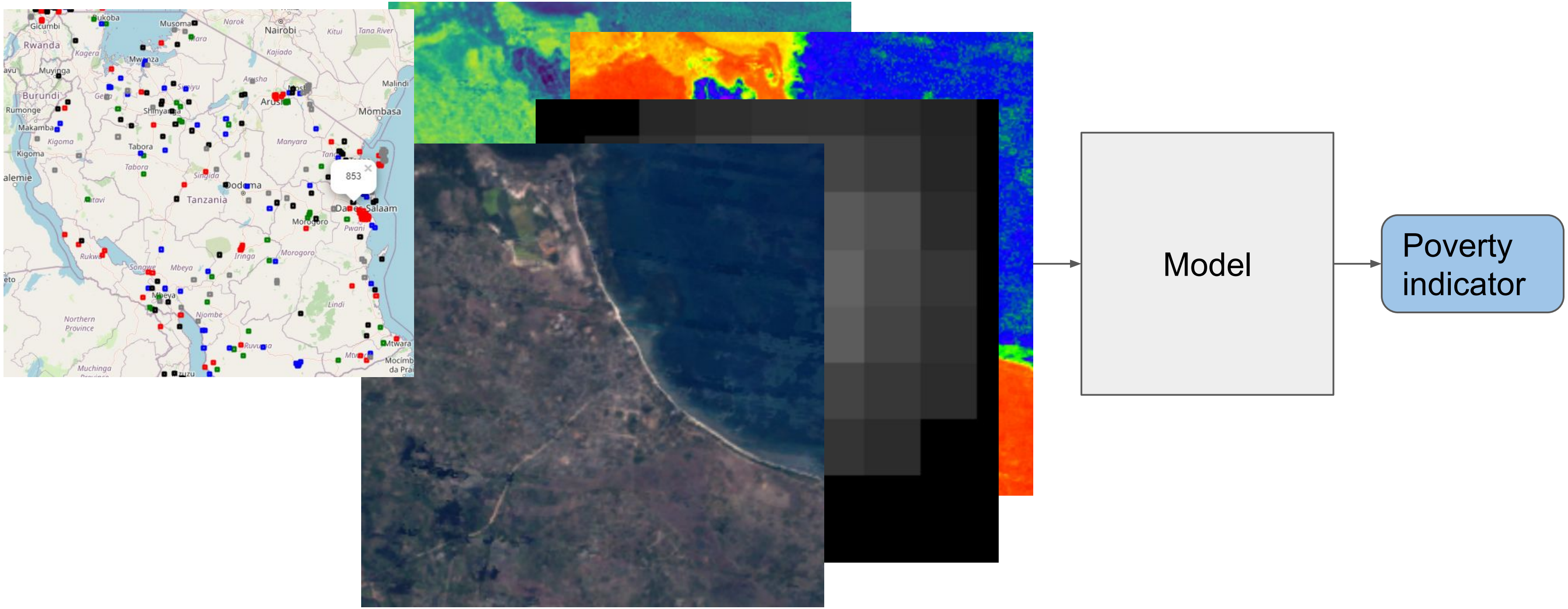
Estimating Poverty with Remote Sensing in Africa



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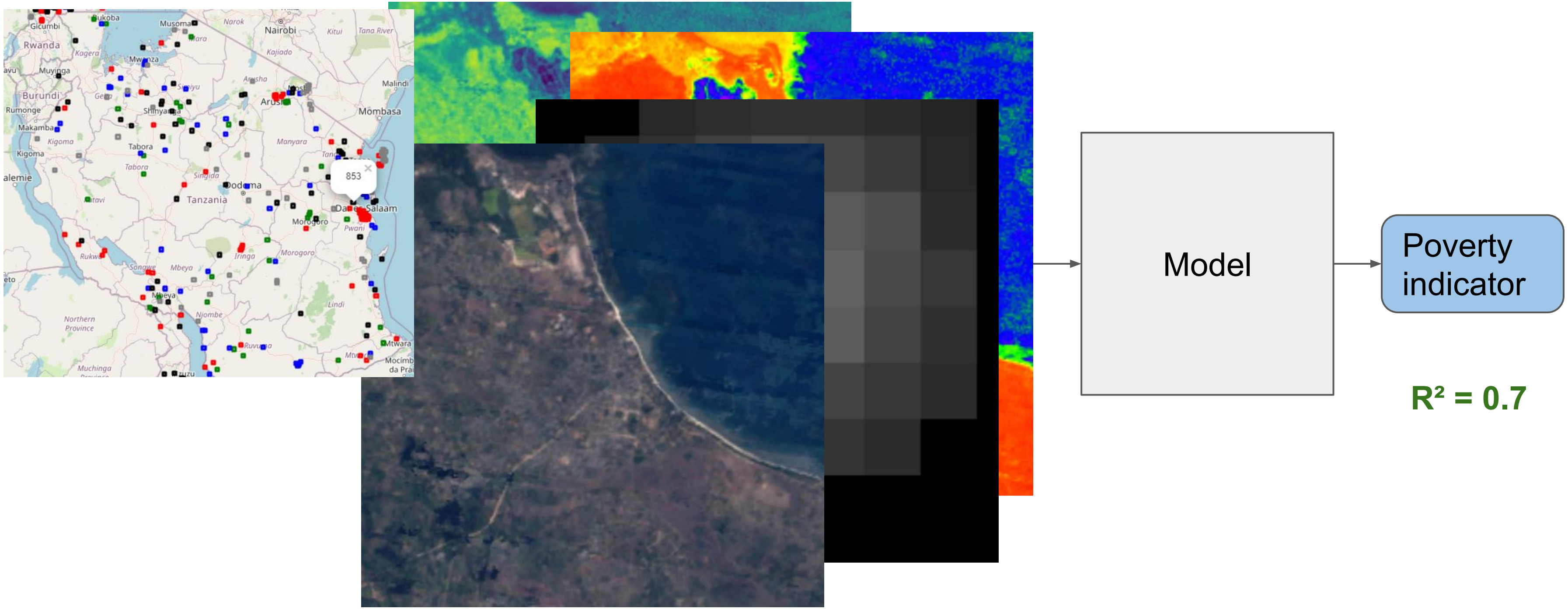
Estimating Poverty with Remote Sensing in Africa



R^2 = 0.7

G. Chi, H. Fang, S. Chatterjee, and J. E. Blumenstock. "Microestimates of wealth for all low-and-middle-income countries" (January 2022). PNAS,Vol 119, No 3.
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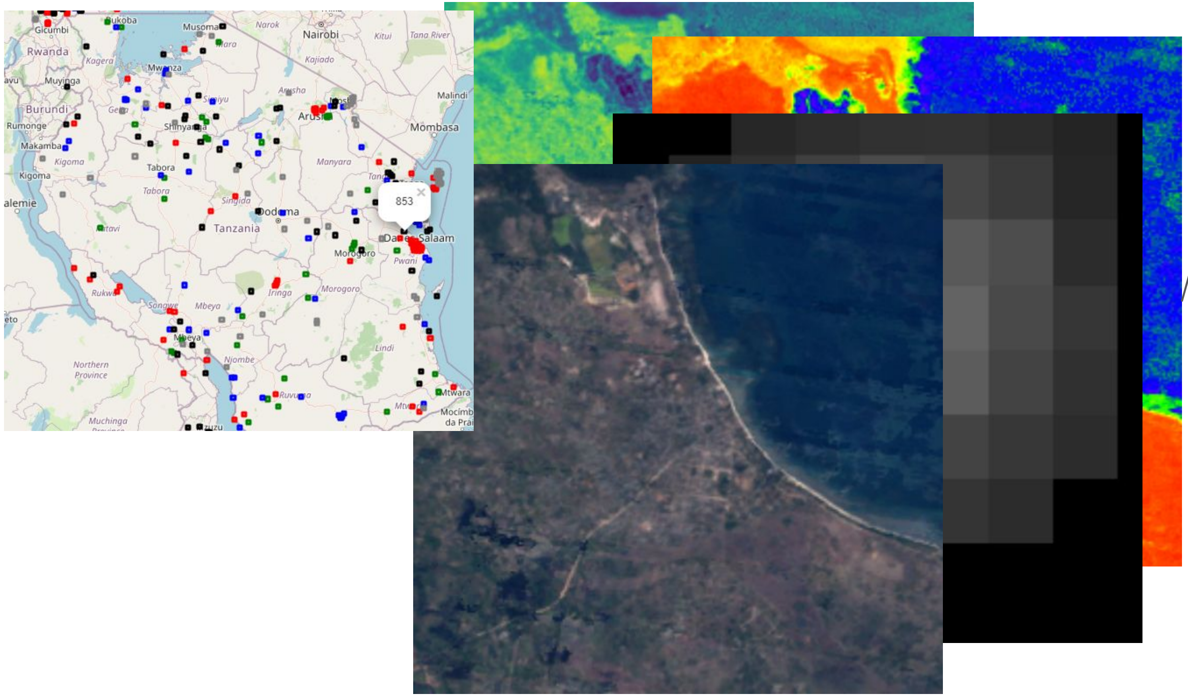
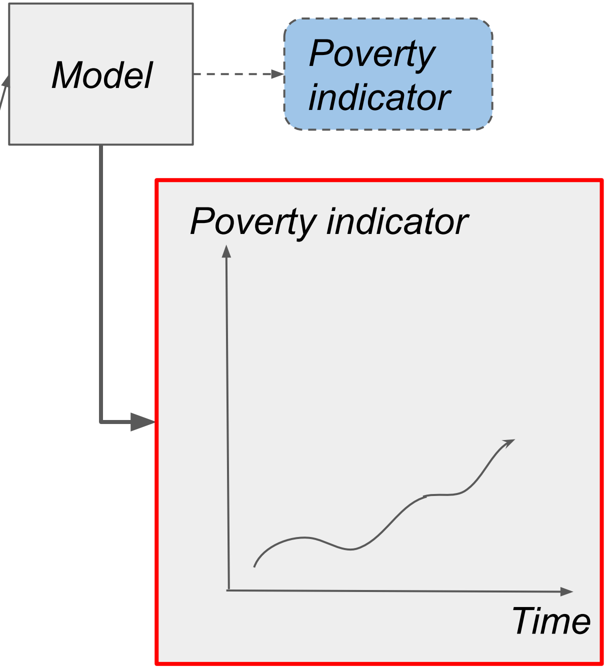
Estimating Poverty *Evolution* with RS in Africa





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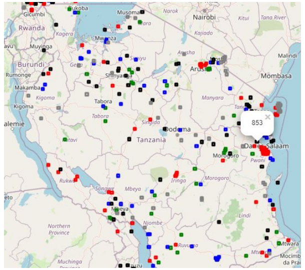
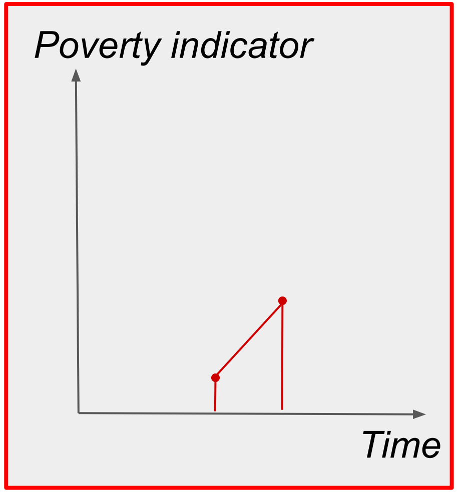
The Problem of Estimating Evolutions

Predicting a Value for Each Time Step

Obs. indicator



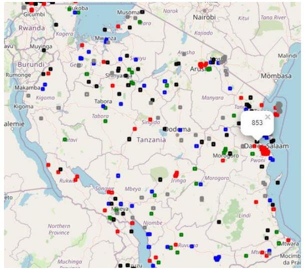


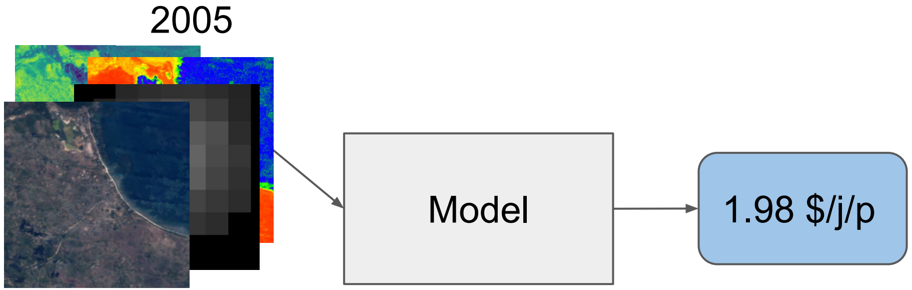
[1]*L. Kondmann, X. X. Zhu. “Measuring Changes in Poverty with Deep Learning and Satellite Images”. 2020 ICLR Workshop : Practical ML for Developing Countries.*

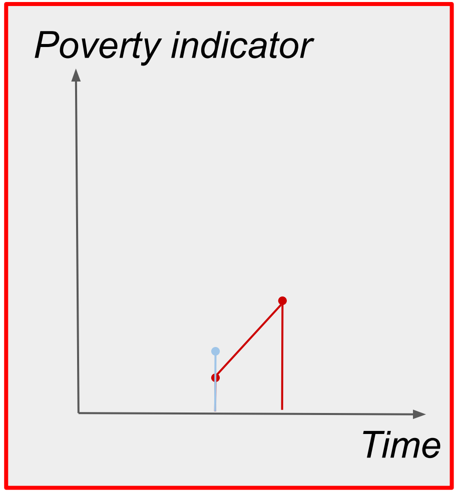
Predicting a Value for Each Time Step

Obs. indicator

Pred. indicator







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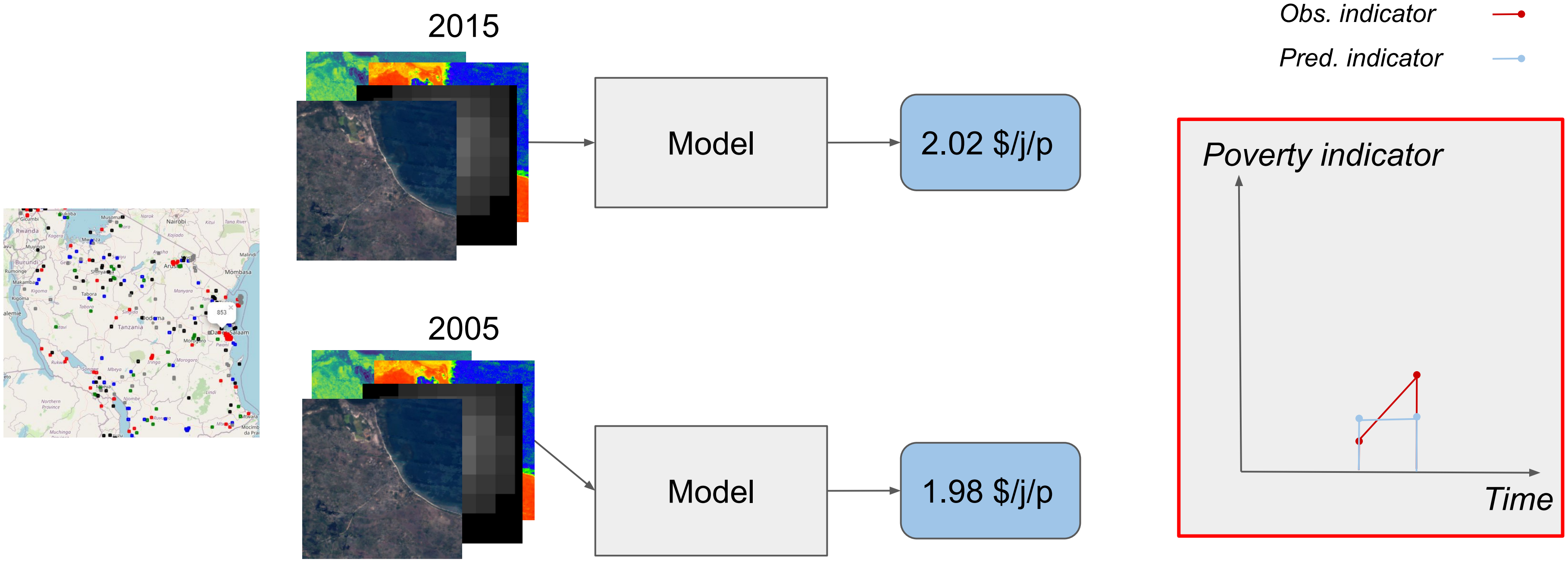
Predicting a Value for Each Time Step



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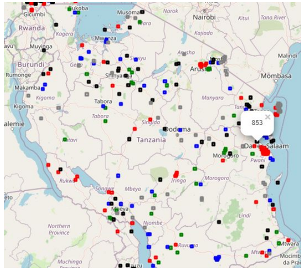
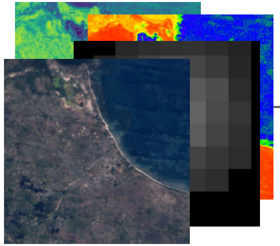


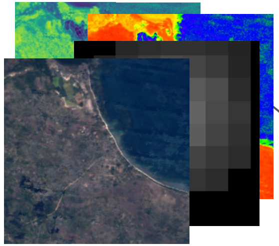
2015



Model

2.02 $/j/p

2005



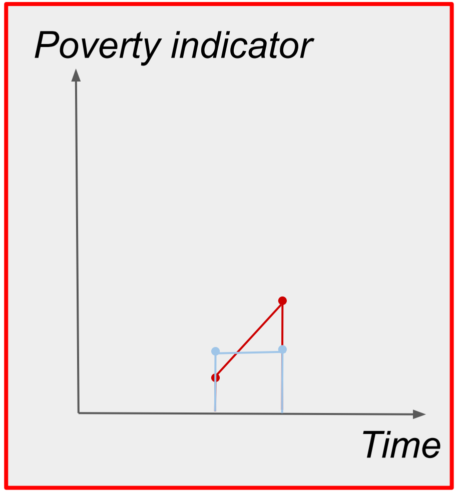
Model

1.98 $/j/p

Subtle changes

Obs. indicator

Pred. indicator



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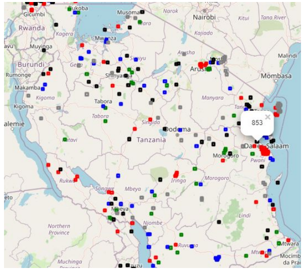
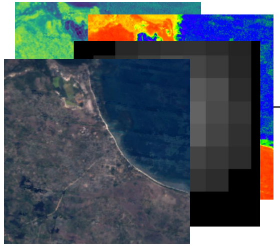
Predicting a Value for Each Time Step



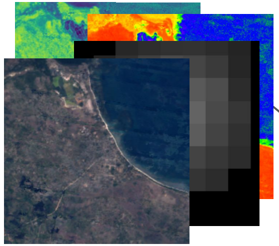
2015



Model

2.02 $/j/p

2005



Model

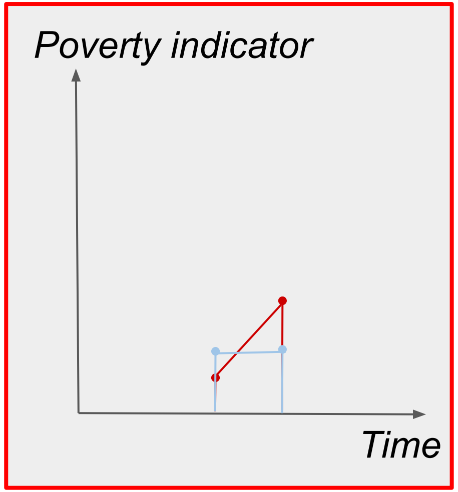
1.98 $/j/p

Subtle changes

Not trained to detect changes

Obs. indicator

Pred. indicator



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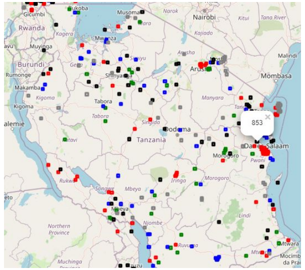
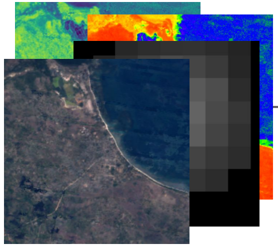
Predicting a Value for Each Time Step

Obs. indicator

Pred. indicator



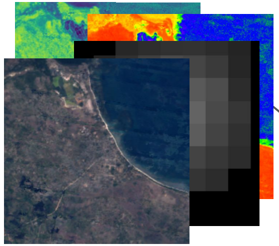
2015



Model

2.02 $/j/p

2005

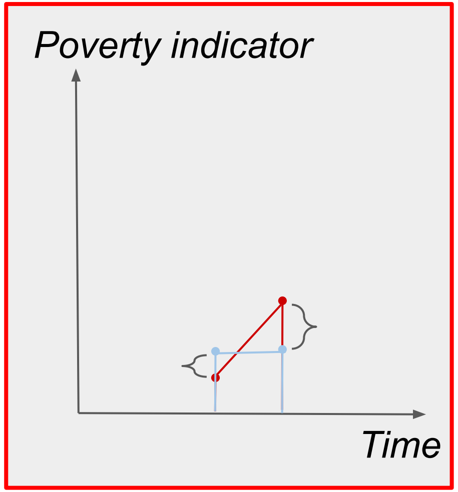


Model

1.98 $/j/p

Subtle changes

Not trained to detect changes



Small individual errors

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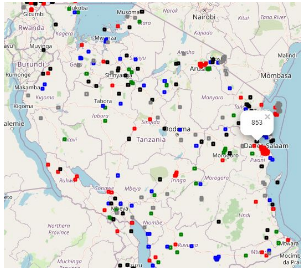
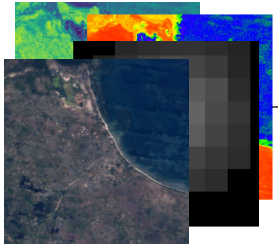
Predicting a Value for Each Time Step

2015

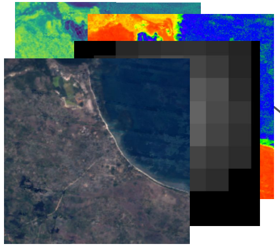




Model

2.02 $/j/p

2005



Model

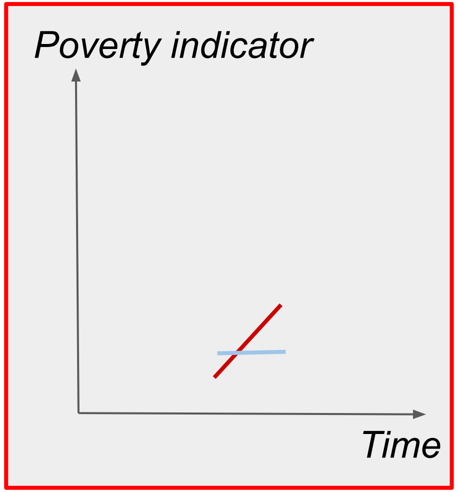
1.98 $/j/p

Subtle changes

Not trained to detect changes

Obs. indicator

Pred. indicator



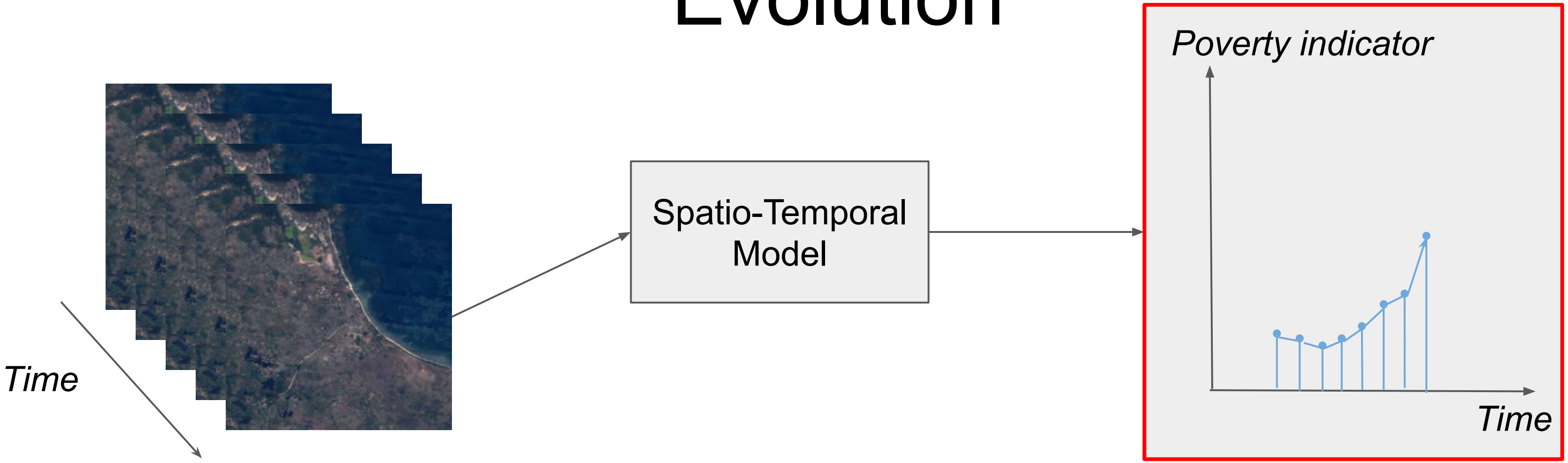
Small individual errors

⇓

Large evolution error

[1]*L. Kondmann, X. X. Zhu. "Measuring Changes in Poverty with Deep Learning and Satellite Images". 2020 ICLR Workshop : Practical ML for Developing Countries.*

Our Work:
Using A Sequence of Images with a Spatio-Temporal Model to Predict the Evolution



Not Enough and Sparse Observed Indicators

Countries with repeated poverty indicator observations[1]

[1]C. Yeh, C. Meng, S. Wang, et al. *"SustainBench: Benchmarks for Monitoring the Sustainable Development Goals with Machine Learning," in Thirty-fifth NeurIPS, Datasets and Benchmarks Track (Round 2), Dec. 2021.*

Not Enough and Sparse Observed Indicators

1665

Countries with repeated poverty indicator observations[1]

Total number of locations[1]

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Not Enough and Sparse Observed Indicators

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Countries with repeated poverty indicator observations[1]

Total number of locations[1]

Not Enough Data

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Countries with repeated poverty indicator observations[1]

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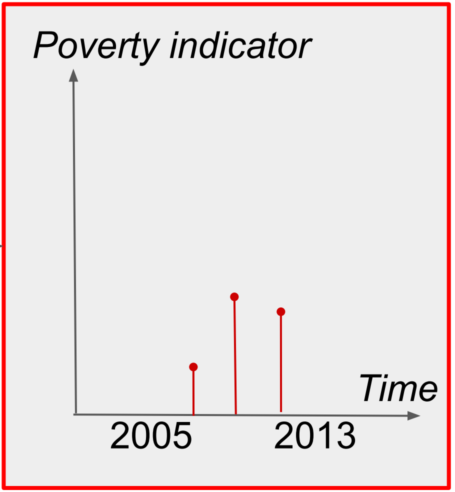
Total number of locations[1]

Not Enough Data



Observed poverty “evolution”

[1] *C. Yeh, C. Meng, S. Wang, et al. “SustainBench: Benchmarks for Monitoring the Sustainable Development Goals with Machine Learning,” in Thirty-fifth NeurIPS, Datasets and Benchmarks Track (Round 2), Dec. 2021.*

Not Enough and Sparse Observed Indicators

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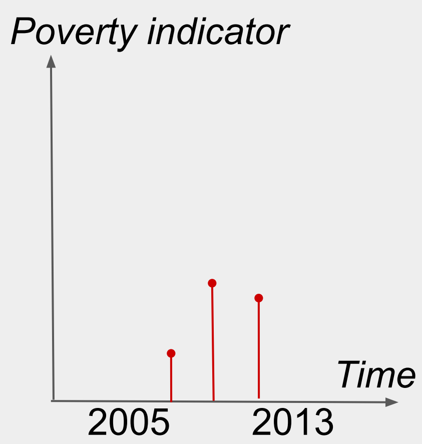


Countries with repeated poverty indicator observations[1]

Total number of locations[1]

Observed poverty "evolution"

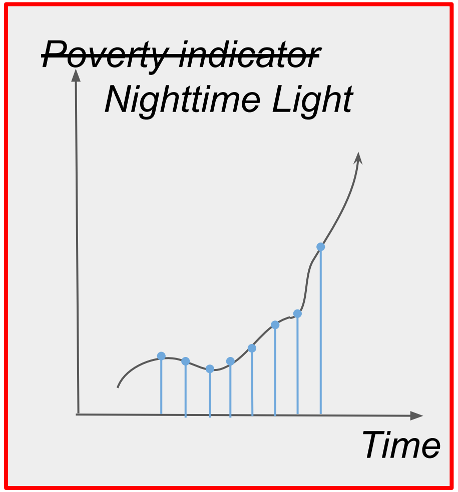
Not Enough Data

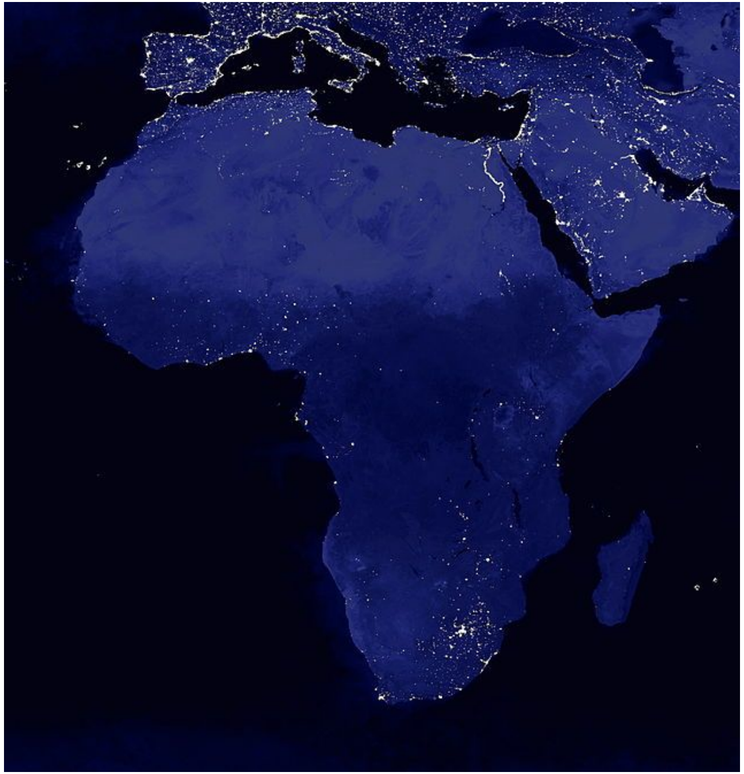
Too small time-window
Sparse and noisy sequence

[1] *C. Yeh, C. Meng, S. Wang, et al. "SustainBench: Benchmarks for Monitoring the Sustainable Development Goals with Machine Learning," in Thirty-fifth NeurIPS, Datasets and Benchmarks Track (Round 2), Dec. 2021.*

Our Alternative: Use Nighttime Light Evolutions as Reference Data

- (Noisy) Proxy for economic activity
- Data available since 1990
- Every year
- Covers the entire globe

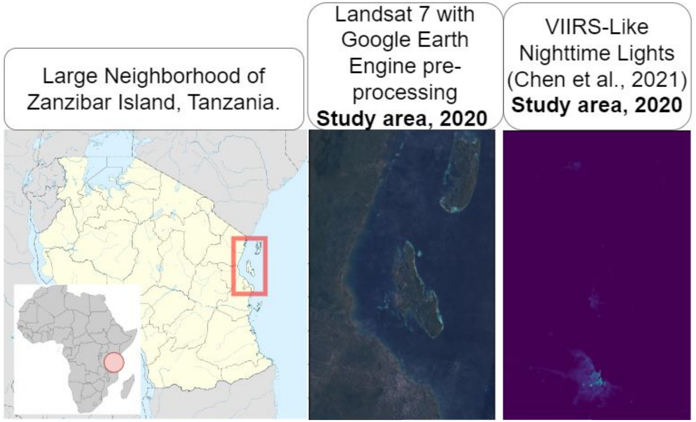




Study Area and Method

Testbed Set Up

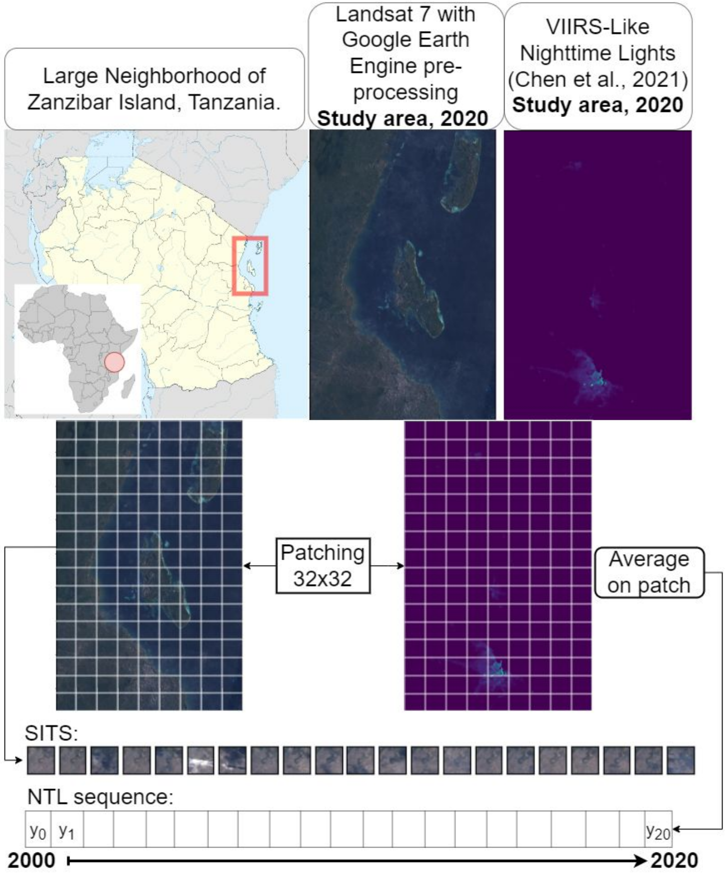
- Landsat-7 (2000-2020) *(B, G, R, NIR, SWIR-1 & 2)*
- VIIRS-like NTL evolutions[1]



[1] *Z.Chen, B.Yu, C.Yang, Y. Zhou, S. Yao, X. Qian, C. Wang, B. Wu, and J. Wu. "An extended time series (2000–2018) of global NPP-VIIRS-like nighttime light data from a cross-sensor calibration". Earth System Science Data. 2021*

Testbed Set Up

- Landsat-7 (2000-2020) *(B, G, R, NIR, SWIR-1 & 2)*
- VIIRS-like NTL evolutions[1]
- Patching strategy :
  - 32×32 grid
  - Pairs of SITS and NTL sequence
- Supervised learning in a 5-fold cross validation set up
- Leave Zanzibar island out for visualization



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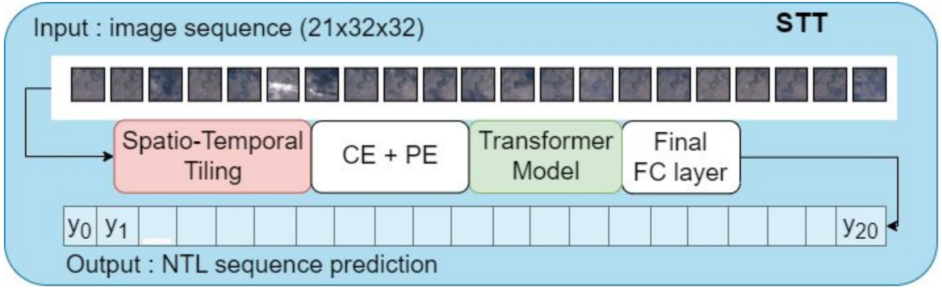
Transformer-Based Models

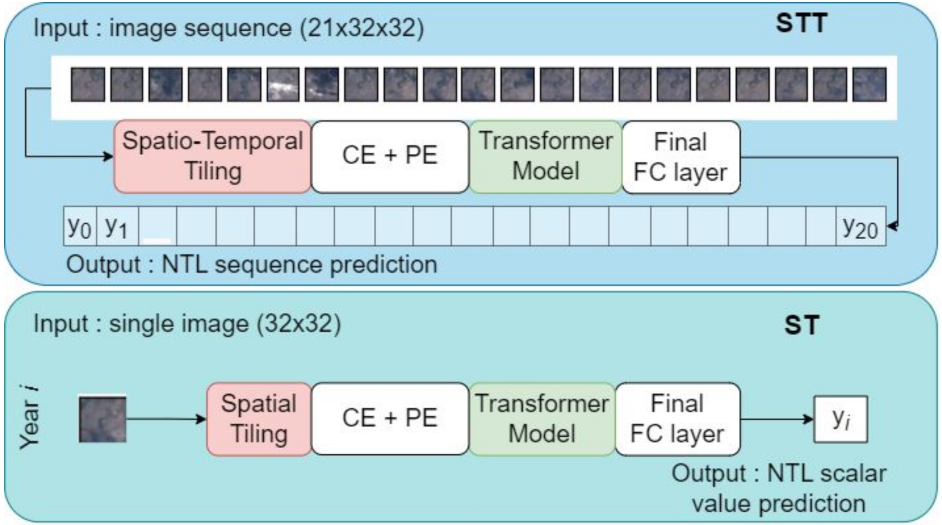
Spatio-Temporal Transformer **(STT)**



Transformer-Based Models

Spatio-Temporal Transformer **(STT)**

Spatial Transformer **(ST)**

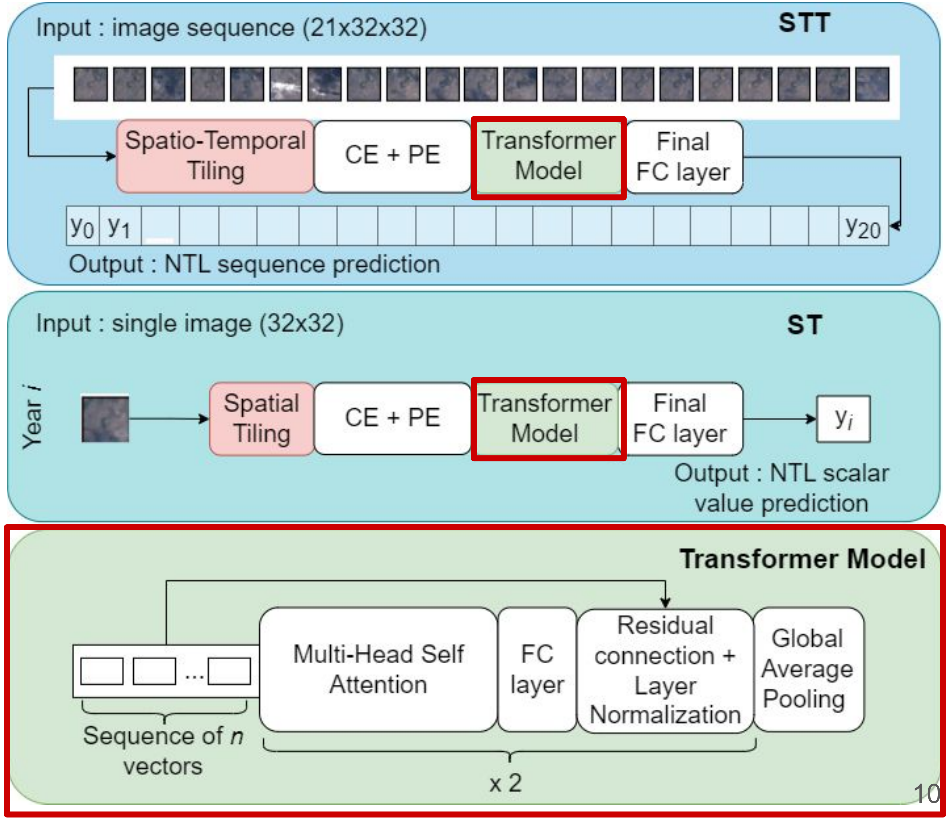


Transformer-Based Models

Spatio-Temporal Transformer **(STT)**

Spatial Transformer **(ST)**

Transformer architecture



Results

How do we Compute the Results

"Per year" Results

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R^2	R^2_0	R^2_1	R^2_2	R^2_3	…

How do we Compute the Results

"Per year" Results

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R²	R^2_0	R^2_1	R^2_2	R^2_3	…

Δt

Evolution Results

Obs	y_0	y_1
Pred	$\hat{y}_0$	$\hat{y}_1$
R²	R^2_0	

How do we Compute the Results

"Per year" Results

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R²	R^2_0	R^2_1	R^2_2	R^2_3	…

Evolution Results

Obs
Pred
R²

Δt

y_1	y_2
$\hat{y}_1$	$\hat{y}_2$
R^2_1	

How do we Compute the Results

"Per year" Results

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R²	R^2_0	R^2_1	R^2_2	R^2_3	…

Evolution Results

Δt

Obs	y_2	y_3	…
Pred	$\hat{y}_2$	$\hat{y}_3$	…
R²	R^2_2		…

How do we Compute the Results

“Per year” Results

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R²	$R^2{}_0$	$R^2{}_1$	$R^2{}_2$	$R^2{}_3$	…

Evolution Results

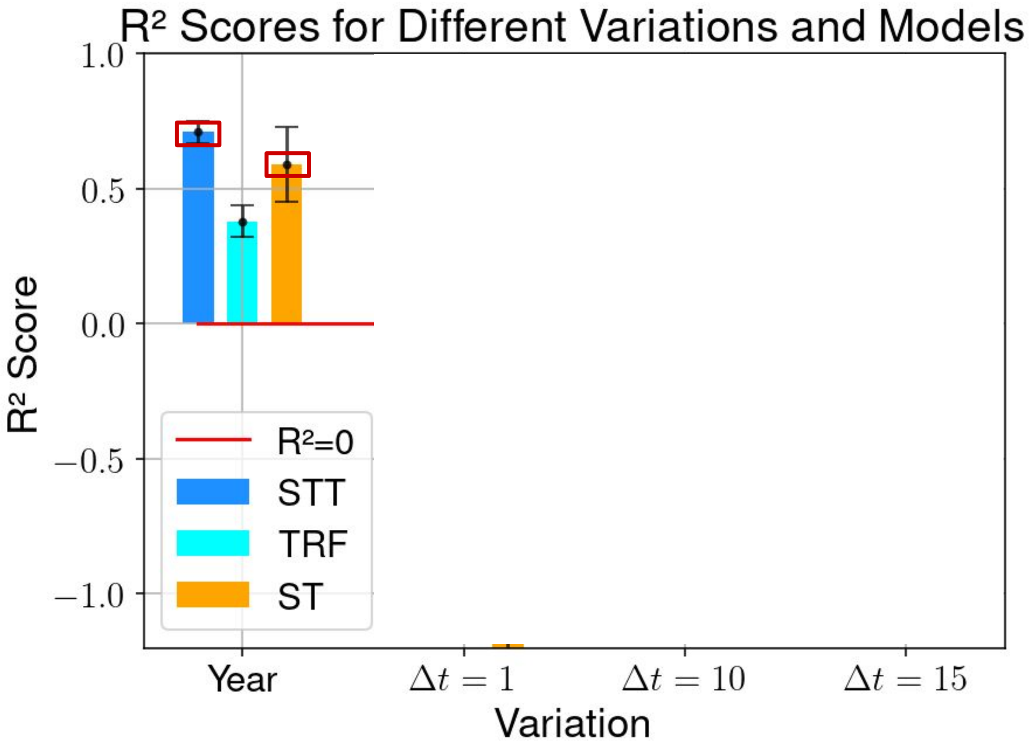
Δt Δt Δt Δt

Obs	y_0	y_1	y_2	y_3	…
Pred	$\hat{y}_0$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	…
R²	$R^2{}_0$	$R^2{}_1$	$R^2{}_2$	$R^2{}_3$	…

Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:

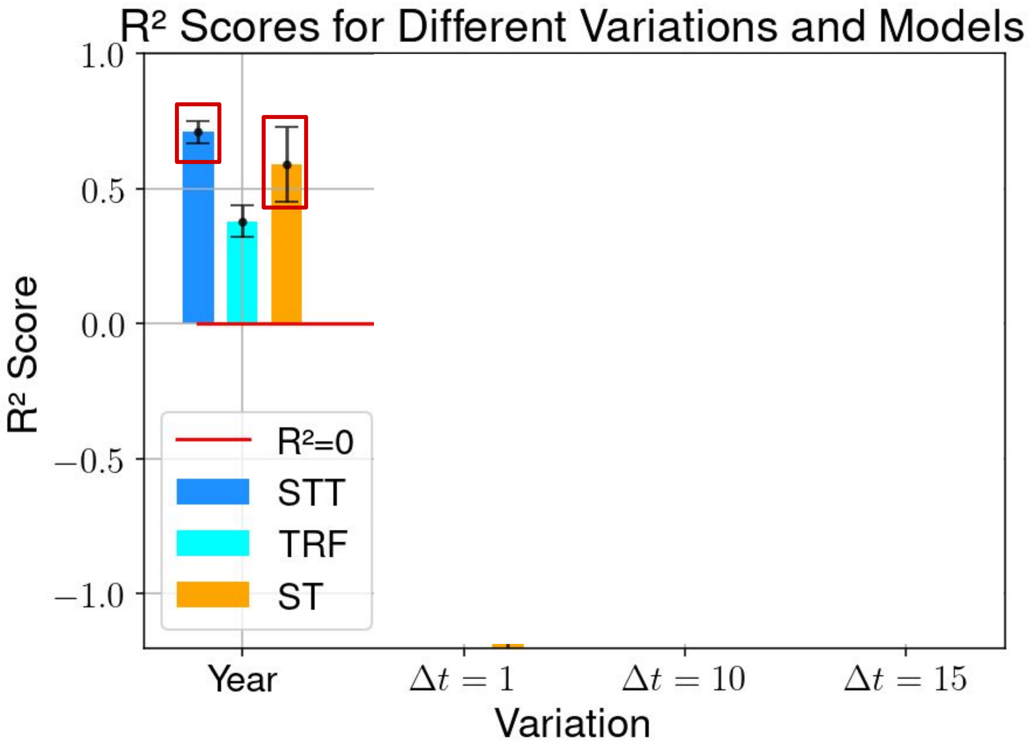
- **STT slightly above ST**



Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:

- *STT slightly above ST*
- **Scores may overlap**



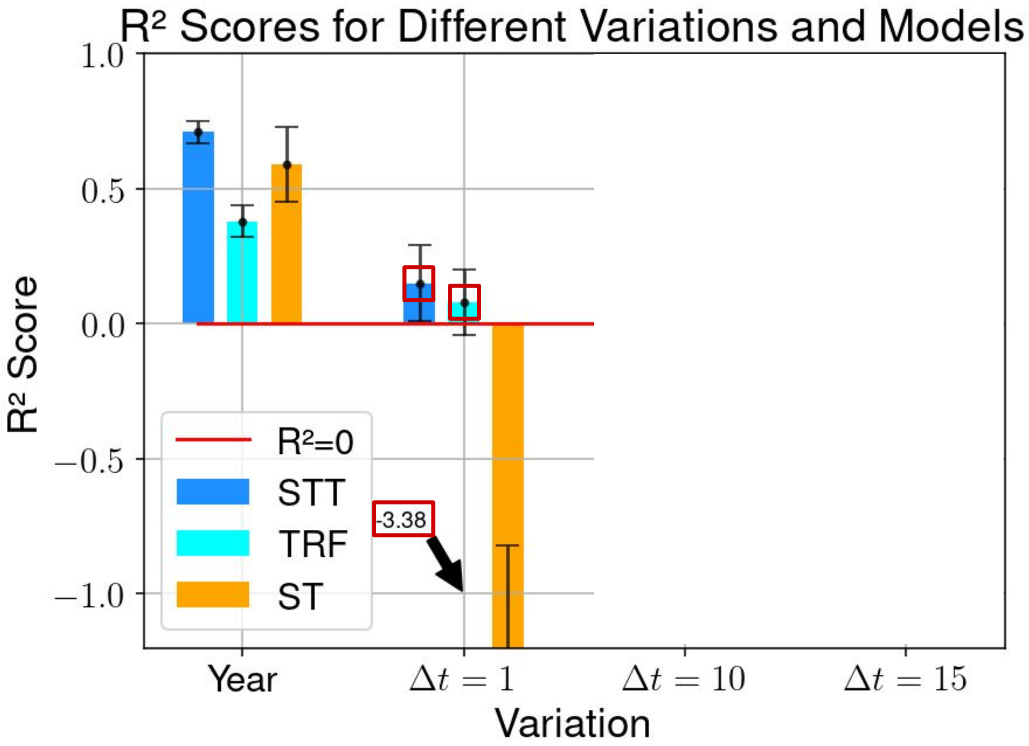
Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:

- *STT slightly above ST*
- *Scores may overlap*

Evolution results:

- **Δt = 1: all models fail**



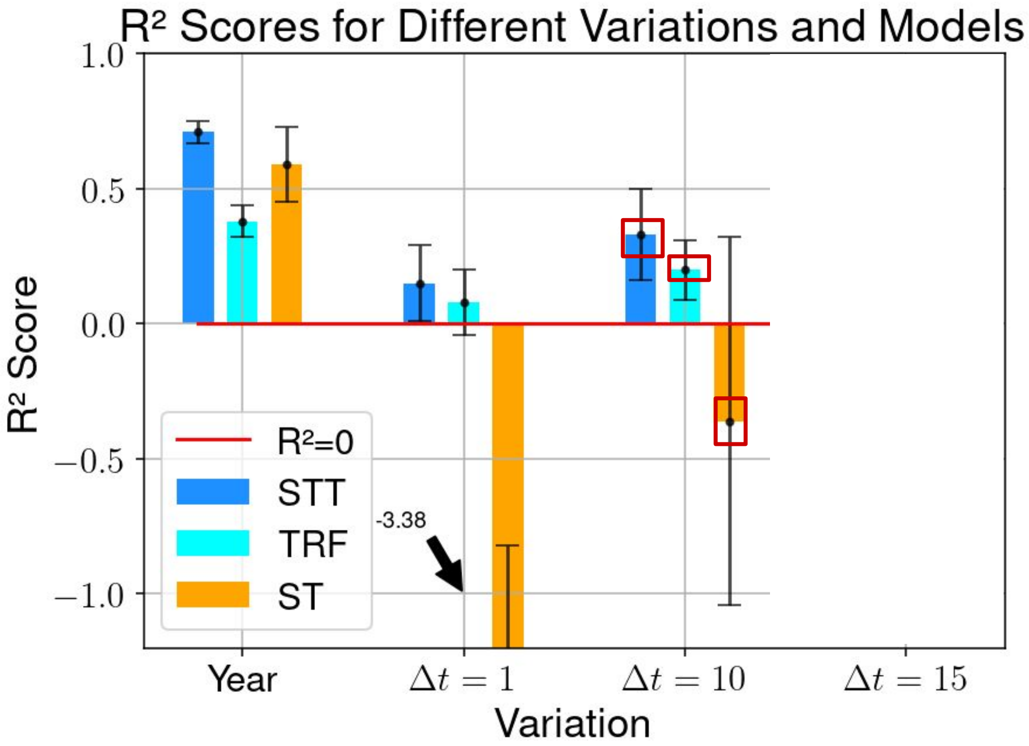
Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:

- *STT slightly above ST*
- *Scores may overlap*

Evolution results:

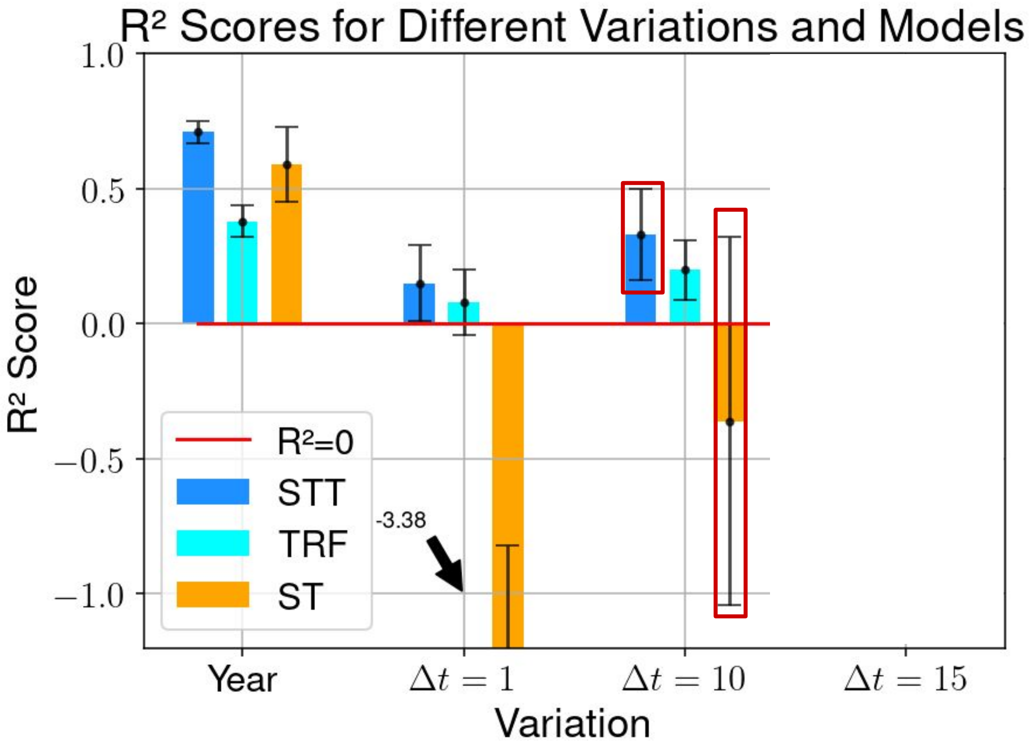
- *Δt = 1: all models fail*
- **Δt = 10:**
  - **Temporal models are better on average**



Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:
- *STT slightly above ST*
- *Scores may overlap*

Evolution results:
- *Δt = 1: all models fail*
- *Δt = 10:*
  - *Temporal models are better on average*
  - **Scores may overlap**



Temporal and Spatio-Temporal Models Outperform Spatial Model

Per year results:

- *STT slightly above ST*
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Evolution results:

- *Δt = 1: all models fail*
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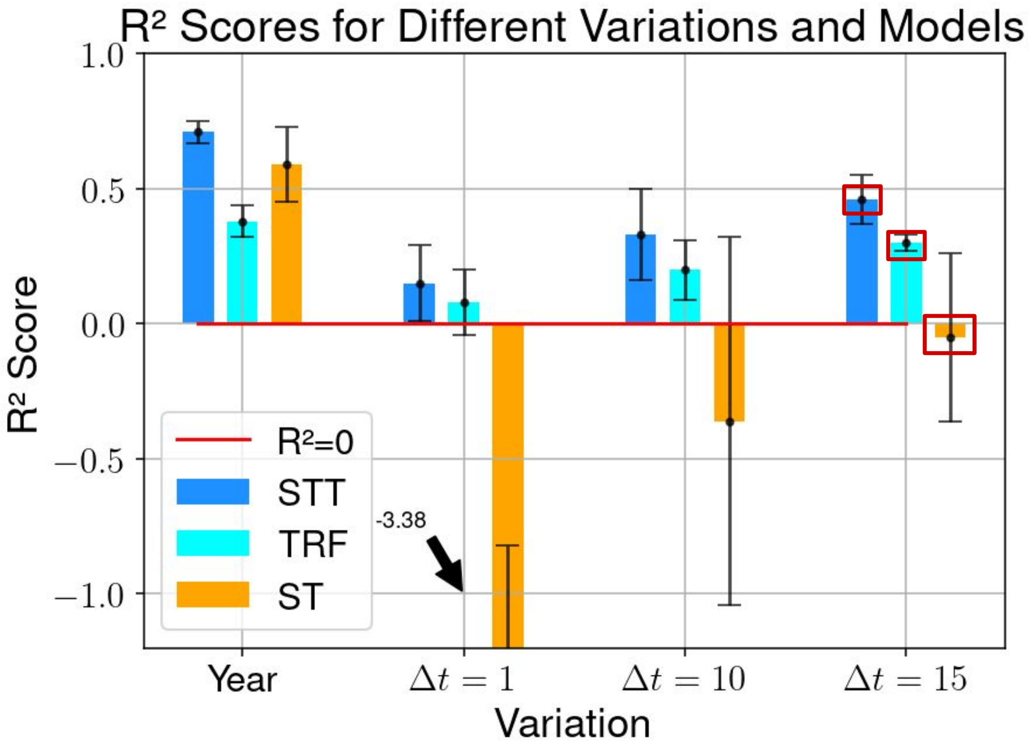

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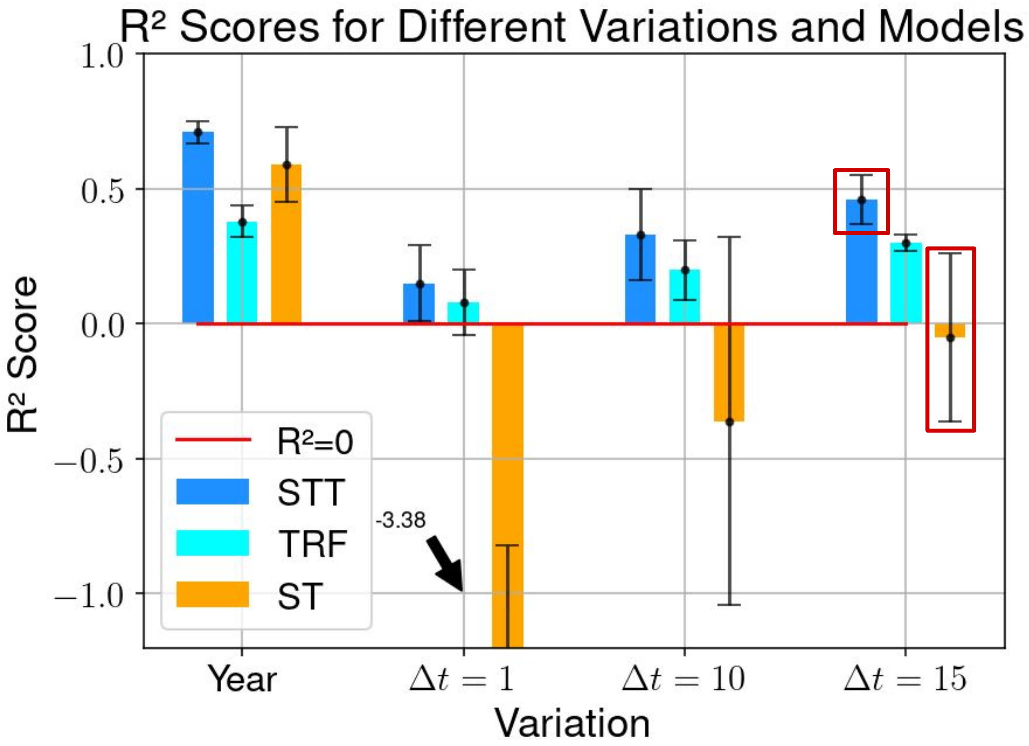

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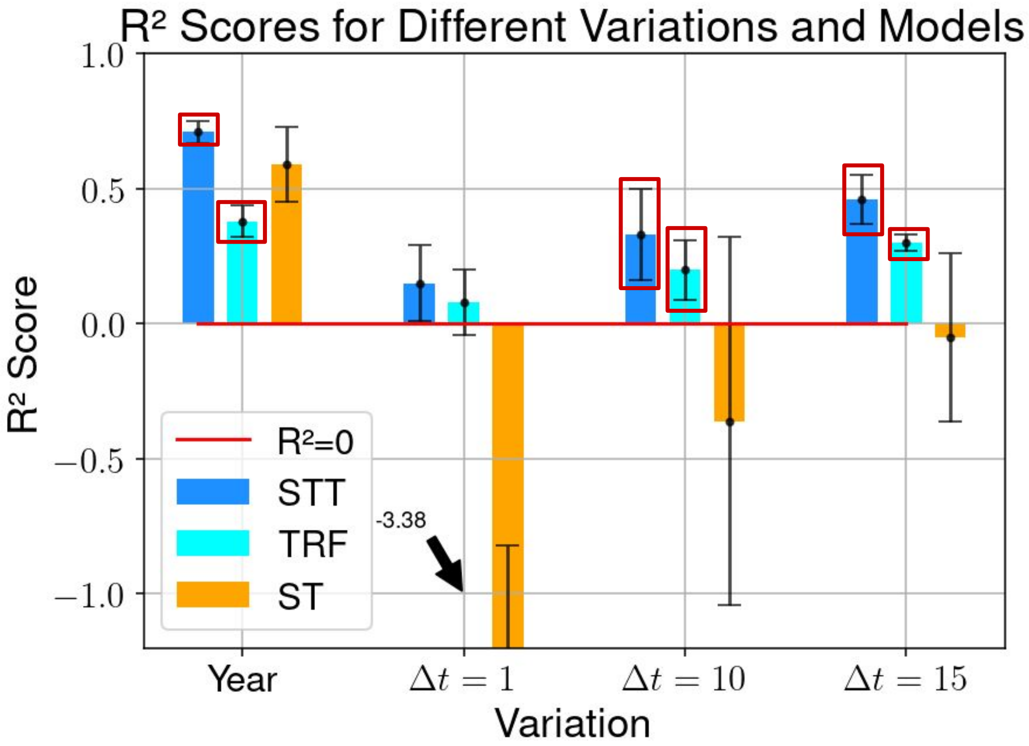
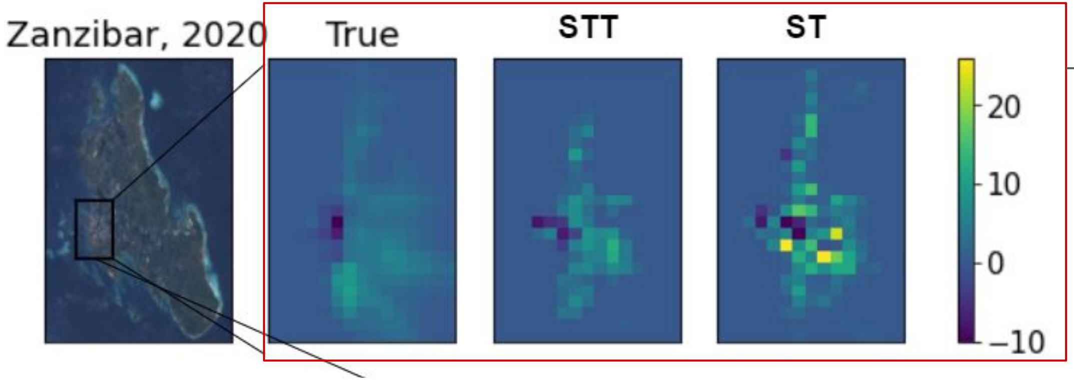


Global result:

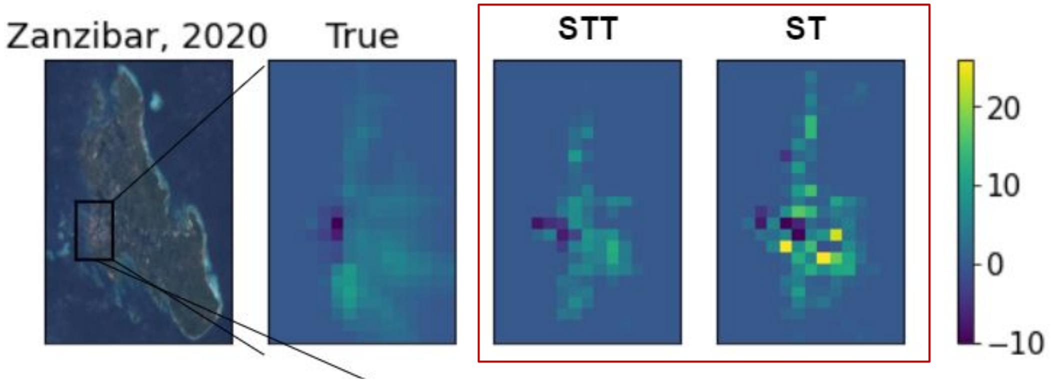
- **Temporal models are more stable**

Held-Out Zone Results



Nighttime light evolution between **2000** and **2020**

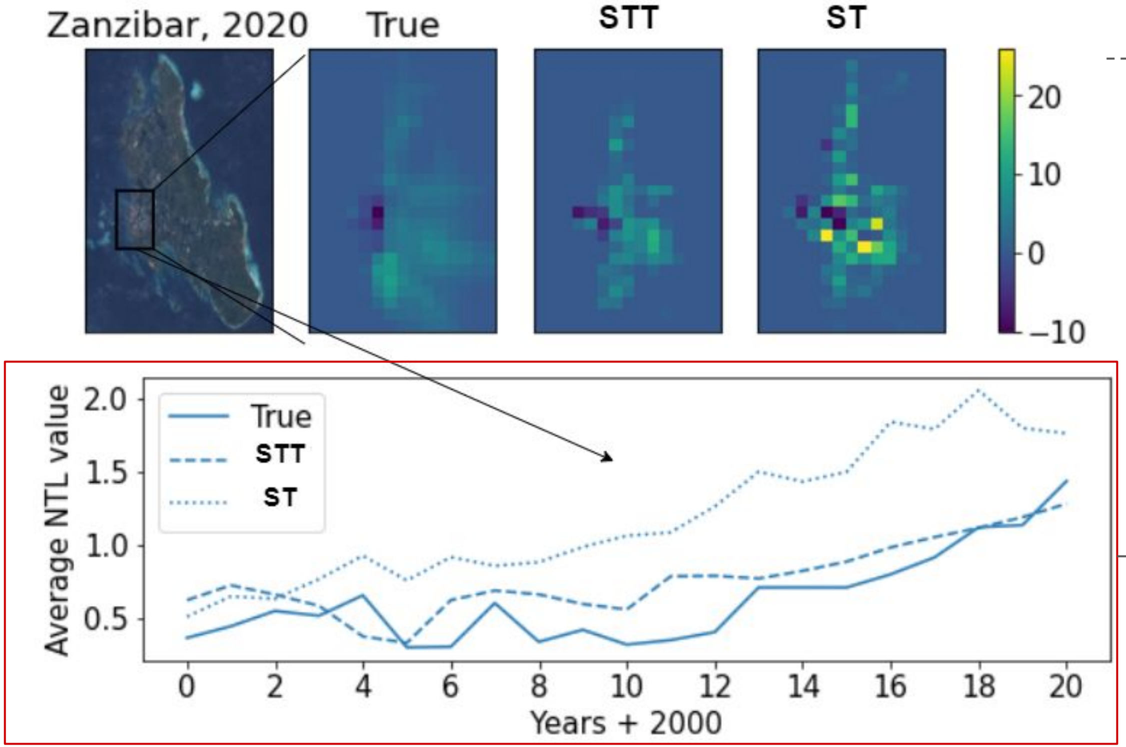
Held-Out Zone Results



Nighttime light evolution between 2000 and 2020

STT seems better than ST in terms of visual homogeneity

Held-Out Zone Results



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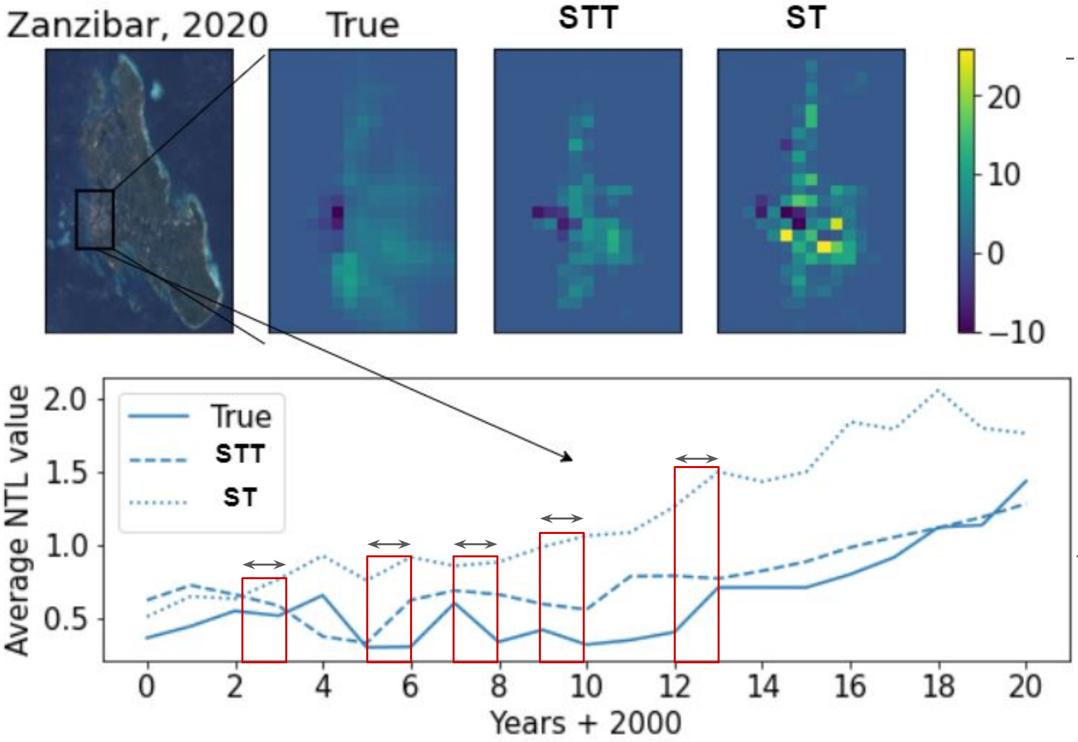

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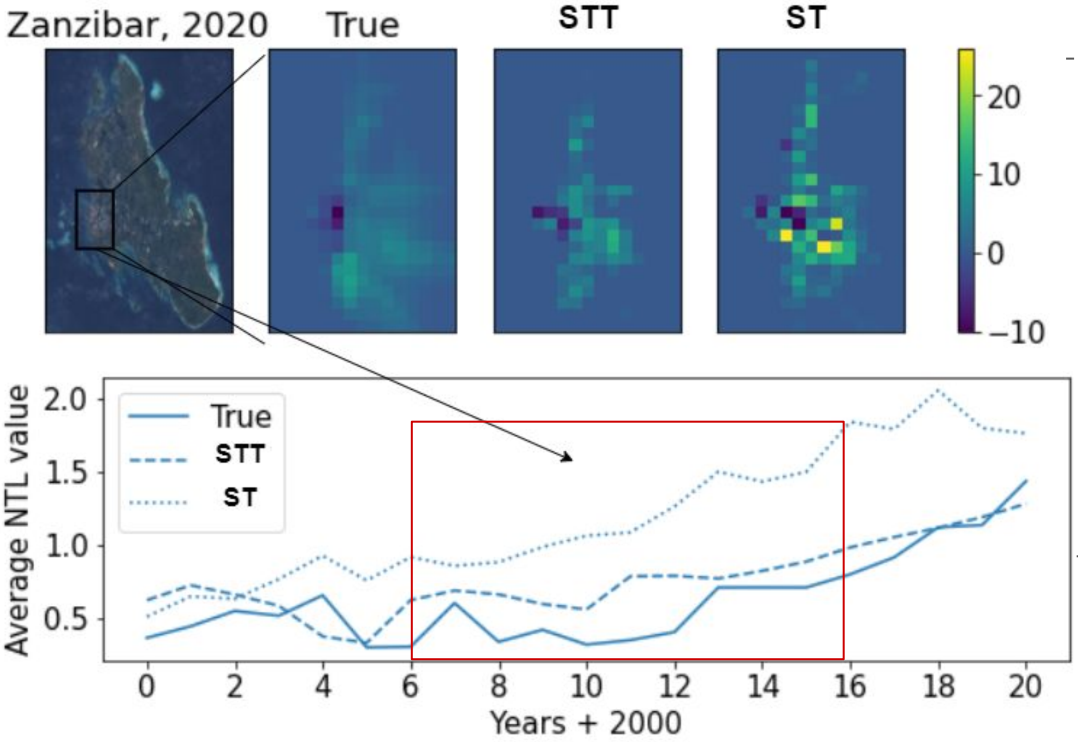

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Conclusion

Spatio-Temporal Models Could Help to Understand Socio-Economic Dynamics

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Future direction:

- Enlarging the study area

Thank you

Funded by :

https://anr.fr/Project-ANR-19-CE03-0005

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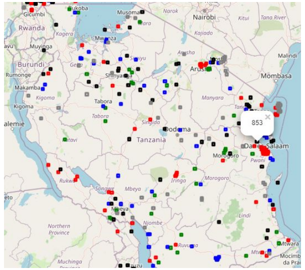
Contact : *robin.jarry@lirmm.fr*

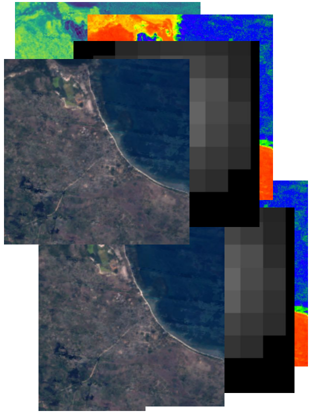
Supplementary Materials

Predicting the Evolution Directly

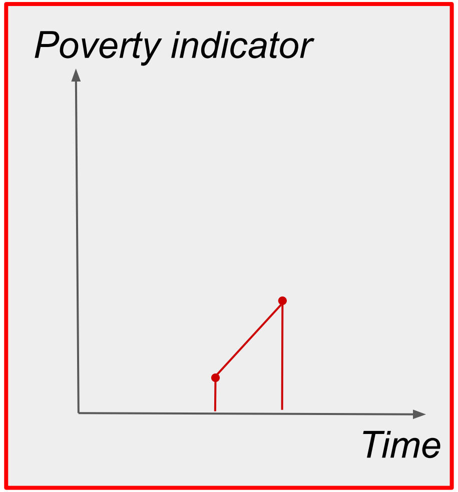
Obs. indicator

2015





2005



[1]C. Yeh, A. Perez, A. Driscoll, et al. “Using publicly available satellite imagery and deep learning to understand economic well-being in Africa” (2020). Nat Commun, Vol 11

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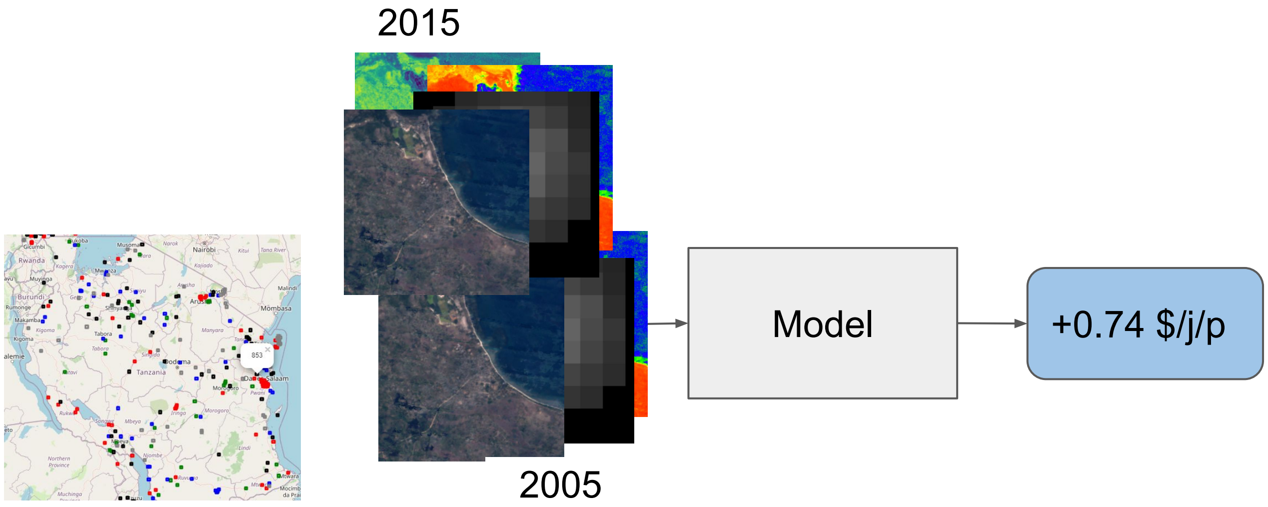

Obs. indicator

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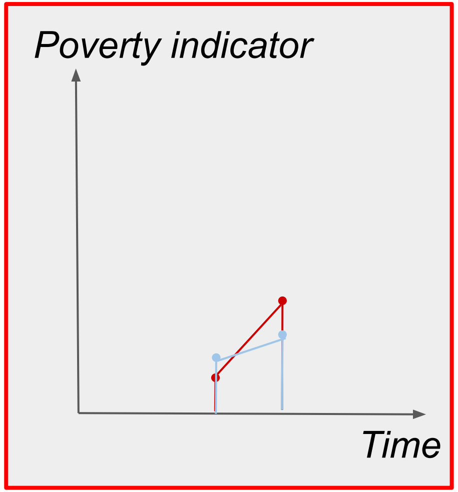

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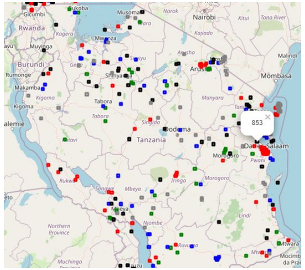

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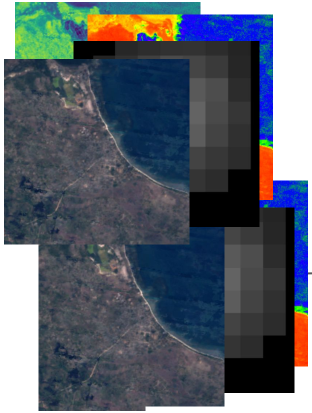


2005

Subtle changes

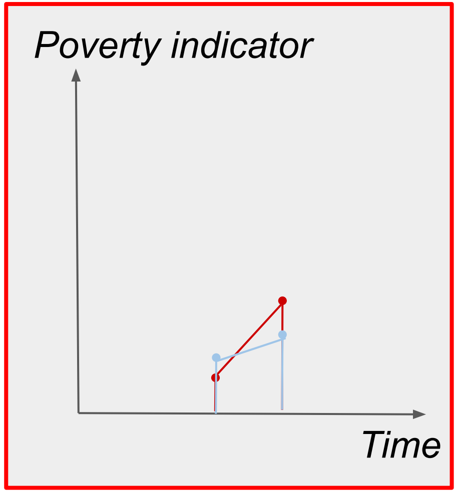
Model

Trained to
detect changes

+0.74 $/j/p

Obs. indicator

Pred. indicator



R^2 = 0.35[1]

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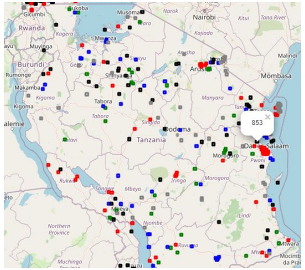

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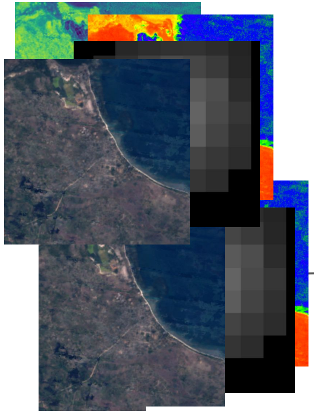

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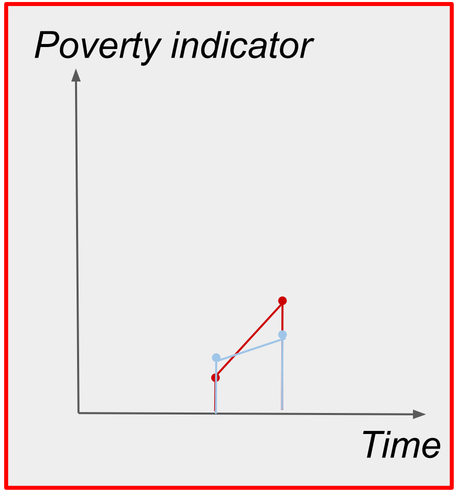

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There is room for improvement

Is Two Time-Steps Enough ?

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How do we Compute the Results

"Per year" Results

$$\overline{R^2} = \frac{1}{21}\sum_{t=2000}^{2020} R_t^2$$

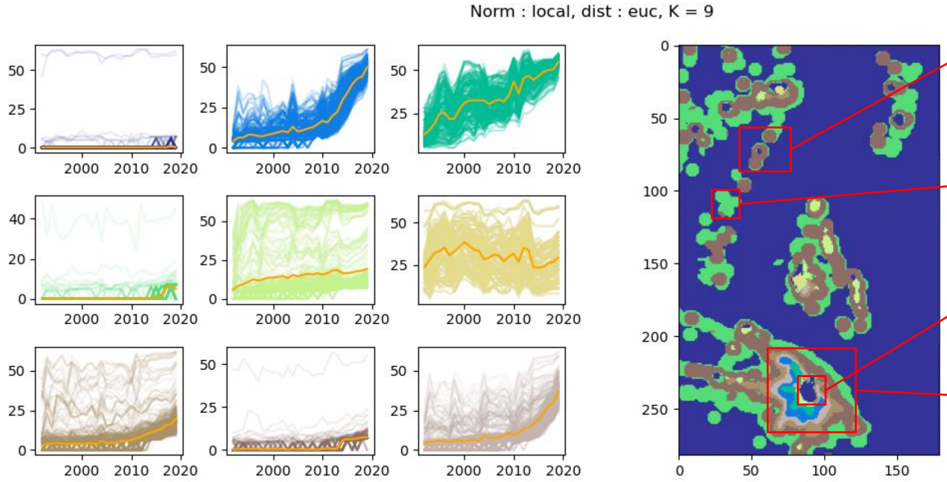
$$= \frac{1}{21}\sum_{t=2000}^{2020} 1 - \frac{\sum_{i=0}^{N}(y_i^t - \widehat{y_i^t})^2}{\sum_{i=0}^{N}(y_i^t - \overline{y^t})^2}$$

Evolution Results (Deltas)

$$\overline{R^2_{\Delta t}} = \frac{1}{21-\Delta t}\sum_{t=2000}^{2020-\Delta t} R^2_{t+\Delta t}$$

$$= \frac{1}{21-\Delta t}\sum_{t=2000}^{2020-\Delta t} 1 - \frac{\sum_{i=0}^{N}\big(\overbrace{(y_i^{t+\Delta t} - y_i^t)}^{\text{Obs. Evolution}} - \overbrace{(\widehat{y_i}^{t+\Delta t} - \widehat{y_i}^t)}^{\text{Pred. Evolution}}\big)^2}{\sum_{i=0}^{N}\big(\underbrace{(y_i^{t+\Delta t} - y_i^t)}_{\text{Obs. Evolution}} - \underbrace{\overline{(y^{t+\Delta t} - y^t)}}_{\text{Avg. Evolution}}\big)^2}$$

Zanzibar, a Large Diversity of Nighttime light Patterns



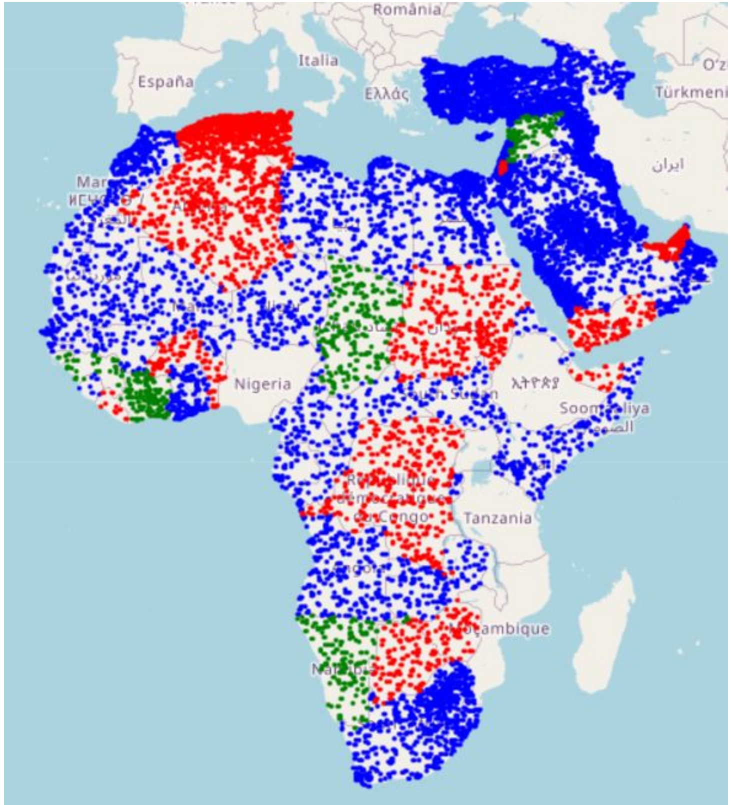
Noise ?

Coastal/rural evolution ?

Urban core evolution ?

Peri-urban evolution ?

Enlarging the study area



The SustainBench : a Source of SDGs Monitoring Dataset

Sustainbench website[1] : https://sustainlab-group.github.io/sustainbench/

Living Standard Measurement Study &
Demographic and Health Survey

Data harmonization between countries
Ready to use in a deep leanring context

[1]*C. Yeh, C. Meng, S. Wang, et al. "SustainBench: Benchmarks for Monitoring the Sustainable Development Goals with Machine Learning," in Thirty-fifth NeurIPS, Datasets and Benchmarks Track (Round 2), Dec. 2021.*