







Understanding Dynamics with Advanced Time-Series **Processing Techniques**

2024 IEEE IGARSS - Time-Series Tutorial









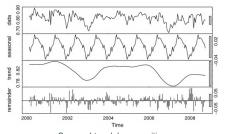
Marc Rußwurm² Dainius Masiliunas² Charlotte Pelletier¹ Jan Verbesselt³ (1) Univ. Bretagne Sud / IRISA, (2) Wageningen University, (3) Belgian Science Policy Office

Contacts: charlotte.pelletier@univ-ubs.fr and dainius.masiliunas@wur.nl

About us

We are working on time series analysis

- unsupervised and supervised learning
- o using machine learning and deep learning techniques
- ◊ in various contexts: large-scale mapping, low supervision, multimodal, etc.



Seasonal-trend decomposition [1] Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, 114(1), 106-115.



The BreizhCrops benchmark datasets https://breizhcrops.org/

About you

We would like to know you better and learn about your expertise.

Please go to menti.com Enter the following code to participate in the survey: 5808 4593



Link to the poll.

Link to the results.

July 7, 2024, from 09:00 to 12:30

Timeline	Торіс
09:00 - 09:15	Part I. Introduction to Time-Series Analysis
09:15 - 09:45	Part II. Time-series segmentation and break detection
09:45 - 10:15	Part III. Deep learning techniques for satellite image time series
10:15 - 10:45	Break
10:45 - 12:00	Practical session: (i) break detection, and (ii) deep learning

Links to all materials available: https://dl4sits.github.io/igarss2024

Content

Opening

Part I. Time-Series Analysis

Time Series

Time Series in Remote Sensing

Part III. Deep learning for Satellite Image Time Series

Time Series Classification

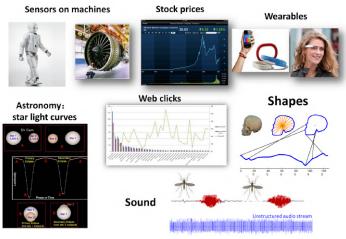
Architectures

Closing remarks

Time Series

Time series

- $\diamond\,$ describe the evolution of a process over time
- ◊ are ubiquitous: daily life, medical, food security, financial, environmental...
- increase in quantity and velocity

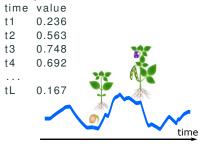


Time Series

Formally, a time series

- is a sequence of values ordered in time
- either univariate or multivariate
- not necessarily regularly-sampled

An example univariate time series:

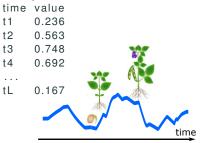


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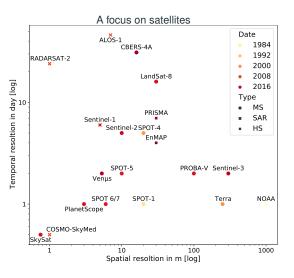
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An example univariate time series:



Time series analysis includes

- unsupervised techniques no prior knowledge on the data
 - clustering: grouping similar time series together
 - ◊ retrieval: finding similar time series
 - segmentation: dividing a time series into "homogeneous" subseries
- supervised techniques requires labelled data (examples)
 - ◊ forecasting: predicting future values
 - ◊ (extrinsic) regression: predicting a continuous scalar variable
 - classification: predicting a category that describes the time series



- ◊ a data increase
- acquisition of data in various modalities
- open access to satellite imagery and archives

Satellite image Time Series (SITS) are

- A stack of images of the same region acquired over time
- that forms a complex datacube
- ◊ (possibly) irregularly sampled.

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The example of crop-type identification



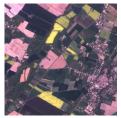
Can you guess where rapeseed grew in this image from May?

http://www.cesbio.ups-tlse.fr/multitemp/?p=1192

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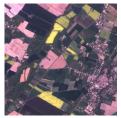
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SITS are crucial to monitoring the Earth's dynamics over large areas

- ◊ landscape changes
- vegetation monitoring
- ◊ landslide analysis

Satellite Image Time Series

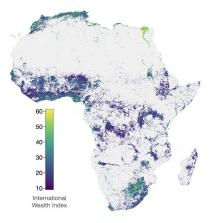
SITS have **various applications** in agriculture, for land cover land use mapping, and soil moisture, vegetation condition or socio-economic indicator estimation.



An example land-cover map of Victoria State, Australia https://tinyurl.com/yc6juv6d



Life fuel moisture content (LFMC) estimation [1]



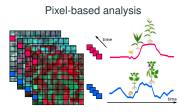
International wealth index (IWI) predictions [2]

[1] Zhu, L., Webb, G. I., Yebra, M., Scortechini, G., Miller, L., & Petitjean, F. (2021). Live fuel moisture content estimation from MODIS: A deep learning approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, 179, 81-91.

[2] Pettersson, M. B., Kakooei, M., Ortheden, J., Johansson, F. D., & Daoud, A. (2023). Time series of satellite imagery improve deep learning estimates of neighborhood-level poverty in Africa. In Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence (pp. 6165-6173).

How to process SITS?

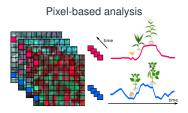
From satellite images to time series



Object-based analysis, *e.g.*, averaging the reflectance values within an agricultural parcel

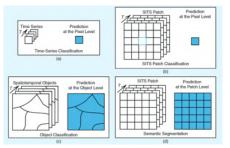
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A taxonomy based on the types of input-output



Time-first, space-later [1]

- o modelling temporal correlations
- ◊ learning dynamics
- ensuring temporal consistency

[1] Camara, G., Assis, L. F., Ribeiro, G., Ferreira, K. R., Llapa, E., & Vinhas, L. (2016, October). Big earth observation data analytics: Matching requirements to system architectures. In Proc. of the 5th ACM SIGSPATIAL International Workshop on Analytics for Big Geospatial Data (pp. 1-6).

- A (very) brief supplement
 - 1. Gather satellite images
 - ◊ THEIA, USGSS, etc.
 - ◊ Sentinels Scientific Data Hub, Copernicus DIAS
 - ◊ cloud platforms: GEE, Amazon, Microsoft Planetary Computer
 - 2. Prepare the data
 - ◊ coregistration, atmospheric correction
 - ◊ gapfilling
 - o normalisation
 - 3. Run your analysis and evaluate it

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- o develop your own Python/R code
- ◊ use dedicated libraries, e.g., snap, OTB, TorchGeo
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Let us now move to the first focus of the tutorial: break detection!

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