

Remote Monitoring of Ground Displacement via Functional Time Series and Conformal Inference

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SAR data are high-resolution images collected by the satellites orbiting around the Earth.

Advanced Interferometric procedures convert raw SAR data into very rich and accurate information on how the ground moves over time.

Differential SAR interferometry (DInSAR) has key potential for natural hazards prevention over large regions.



Vertical ground displacement over the Phlegraean Fields, Italy, on May 11, 2024, in coherent pixels, cumulated with respect to the reference time March 16, 2015.







High-dimensional interferometric data

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Temporal series of vertical ground displacement over the Phlegraean Fields, Italy, from November 16, 2020, until May 11, 2024. The vertical ground displacement is cumulated with respect to the reference time of March 16, 2015, and is only displayed in coherent pixels.



General methodological framework

 Y_1, \ldots, Y_n time series s.t. $Y_i: \Omega \to L^2(D), D \in \mathbb{R}^2$. Y_{n+1} is a new observation of the time series.

Nonparametric statistical monitoring of ground displacement

Historical information

New observation











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Conformal prediction band at level α

 $C_{1-\alpha}(Y_{1:n})$ $= \{ y \in L^{2}(D) : y(u, v) \in [\hat{\mu}(u, v) \pm Q_{1-\alpha}(u, v)], \forall (u, v) \}$

• $\hat{\mu}(u, v)$ point predictor at coordinates (u, v),

 $Q_{1-\alpha}(u,v)$ threshold at (u,v) calibrated for α .

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Lower bound at 10%



Upper bound at 10%











Conformal dicotomic warning map

Given a history $Y_1, ..., Y_n$ and a new observation Y_{n+1} , the conformal dicotomic warning map for Y_{n+1} is

 $w_{n+1}(u,v) = \begin{cases} 0, & Y_{n+1} \in C_{1-\alpha}(Y_{1:n}; u, v) \\ 1, & Y_{n+1} \notin C_{1-\alpha}(Y_{1:n}; u, v) \end{cases}$







Dicotomic warning map

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Guarantees

Thanks to the conformal guarantees, we have that when Y_{n+1} is not an anomaly

$$\mathbb{P}[\exists (u, v) : w_{n+1}(u, v) = 1] \le \alpha$$







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Main advantages

- No assumption on the data distribution •
- Localization of the anomalies •
- Control the risk of false warnings



Dicotomic warning map

Dicotomic warning map at 2023-06-10



Dicotomic warning map for June 10, 2023. The pixels where the map takes value 1 are considered as anomalies and are colored in red. The remaining pixels are considered as in-control. From Bortolotti, Casu, Virelli, Tapete, Siciliani de Cumis, Menafoglio, Vantini (2024). Congress Proceedings of the 75th International Astronautical Congress.

Longitude





P-value warning map

Fix the point (u, v) and consider a univariate setting.

Inspiration: Classical point-wise p-value

Given a history $Y_1(u, v), ..., Y_n(u, v)$, the point-wise p-value of a new observation $Y_{n+1}(u, v)$ is

$$p_{n+1}(u, v) = \max_{\alpha} \alpha$$

s.t. $Y_{n+1}(u, v) \in PI_{1-\alpha}(Y_{1:n}(u, v))$





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$$\mathsf{Y}_{\mathsf{n}+1}$$
 and $\mathsf{C}_{\mathsf{1}-\alpha}(\mathsf{Y}_{\mathsf{1}:\mathsf{n}})$



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P-value warning map

P-value warning map at 2023-06-10



P-value warning map for June 10, 2023.

Longitude





Continuous monitoring over time

Pointwise empirical coverage of prediction bands in 2023



Empirical coverage map at 10%.



Timeline of detected anomalies.



Key aspects of the proposed monitoring tool

- Assumption-free approach
- Integration of spatial and temporal dynamics of ground displacement
- Localization of the anomalies
- Controlled risk of false warnings

Future extensions of the monitoring tool

- Joint monitoring of higher order derivatives
- Adaptation of the tool to account for noisy ground displacement observations
- Filling of the information in incoherent pixels



Thank you!

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