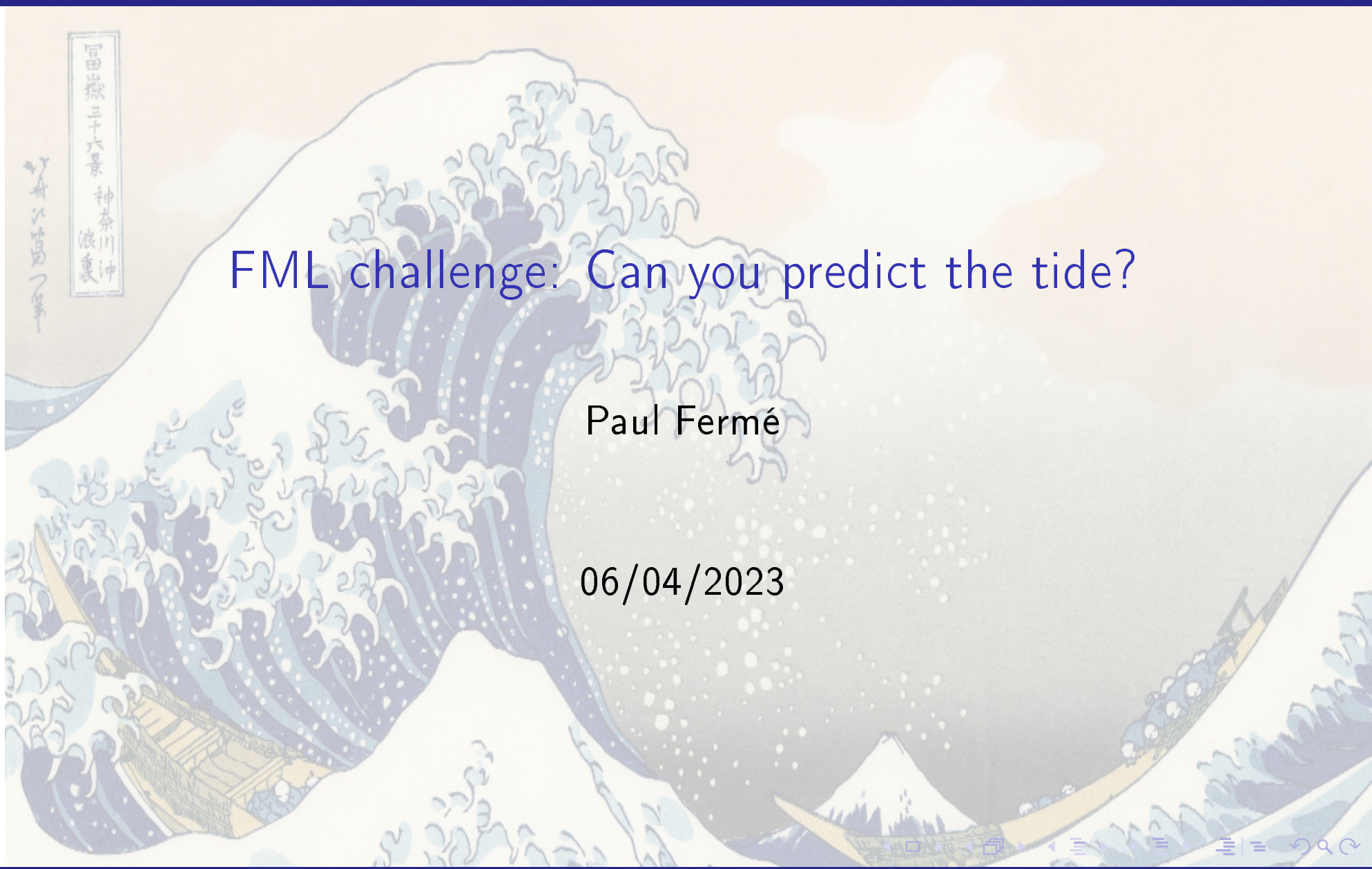

# FML challenge: Can you predict the tide?

Paul Fermé

06/04/2023

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- Variations of sea level composed of *tide* and *surge*.

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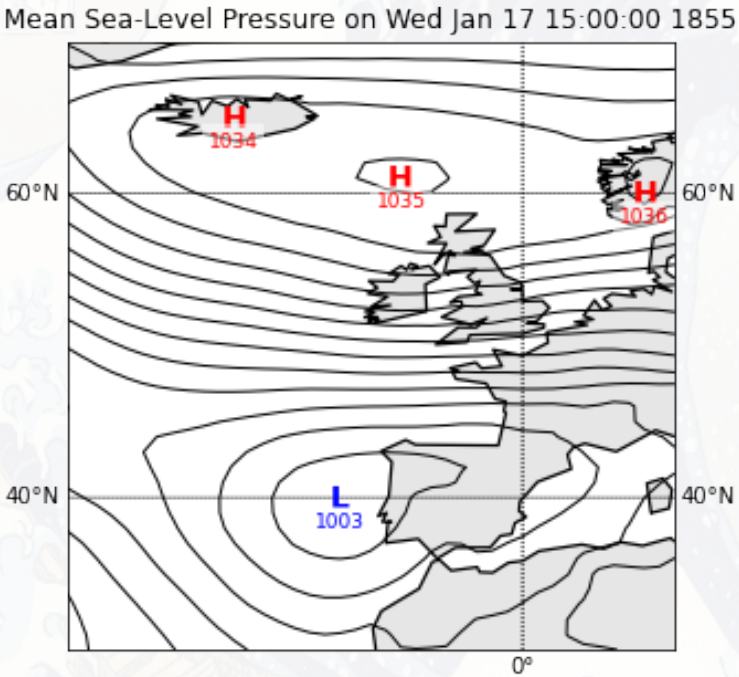
- *Surge* is the difference between observed sea level and *tide*. *Critical importance for safety reasons.*

# Data description

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- Sea surges of two (unknown) cities.

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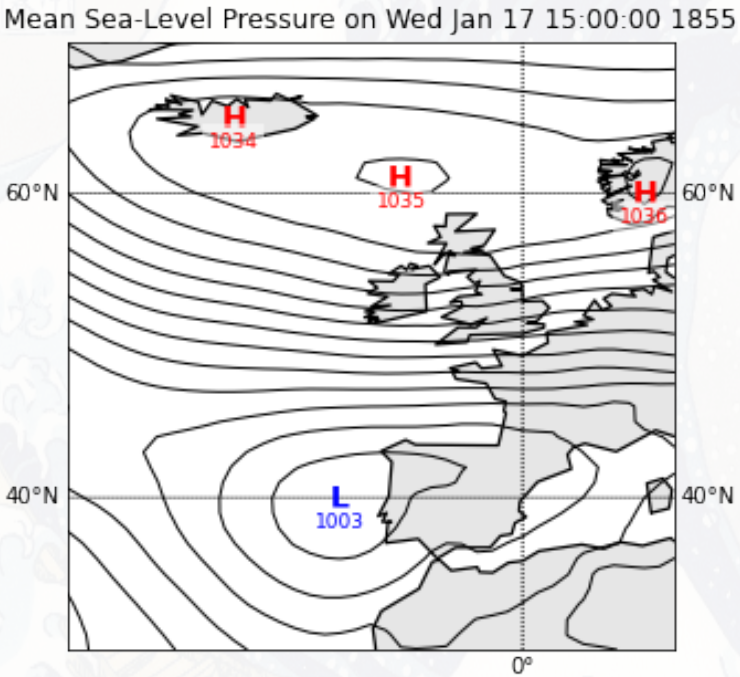


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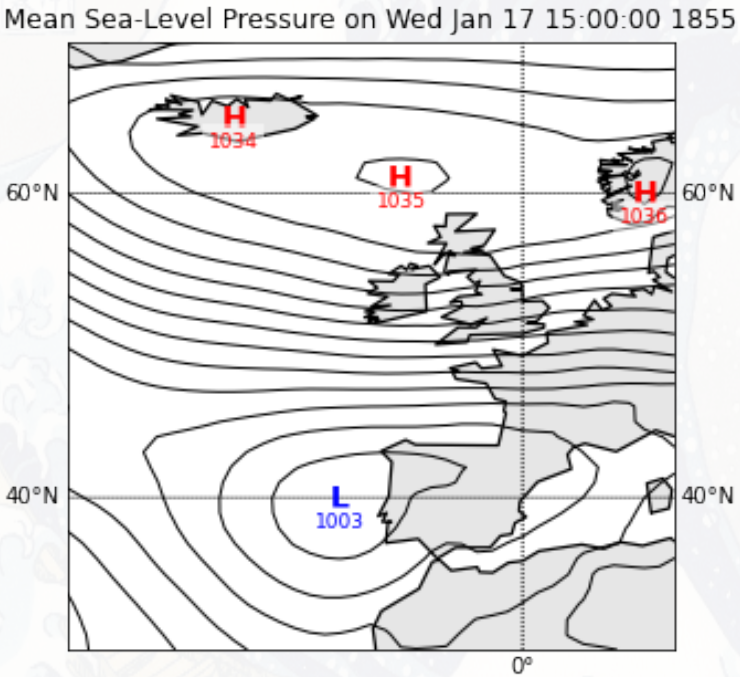


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- Output: Surges on next five days.

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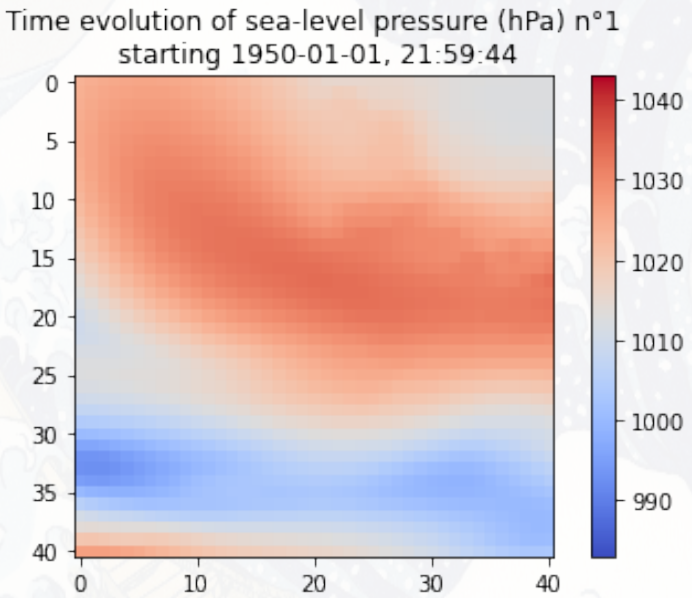
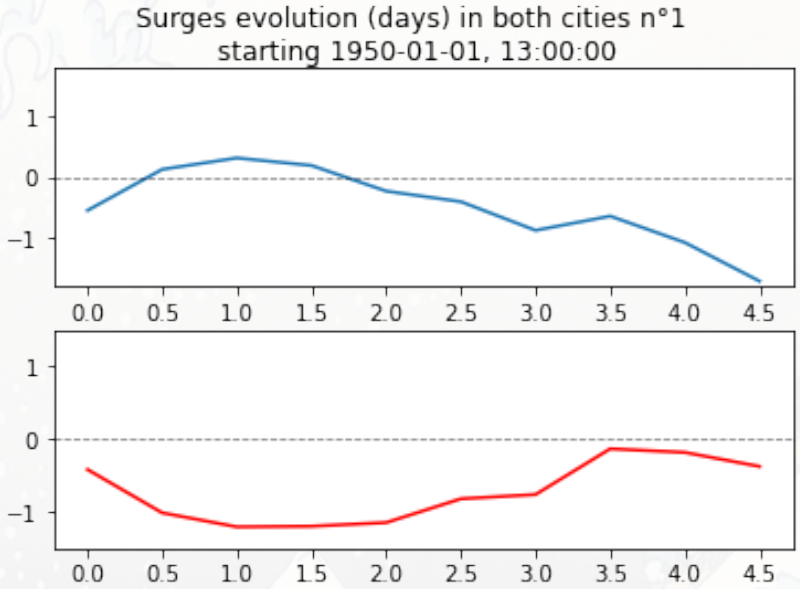
Input:



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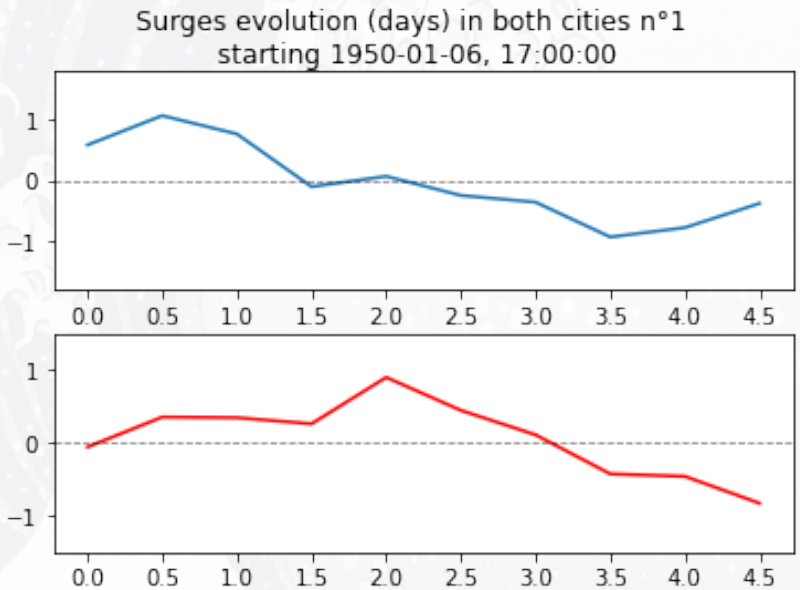

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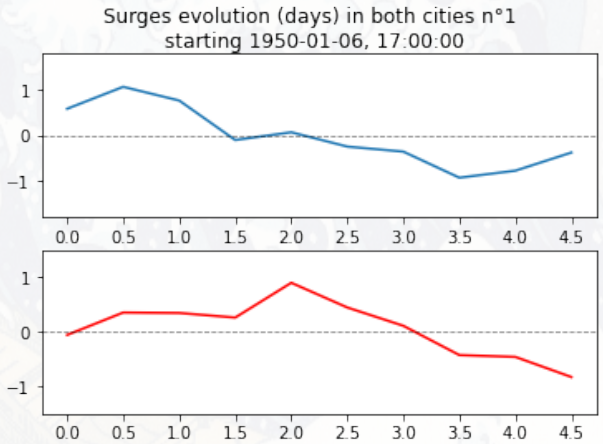
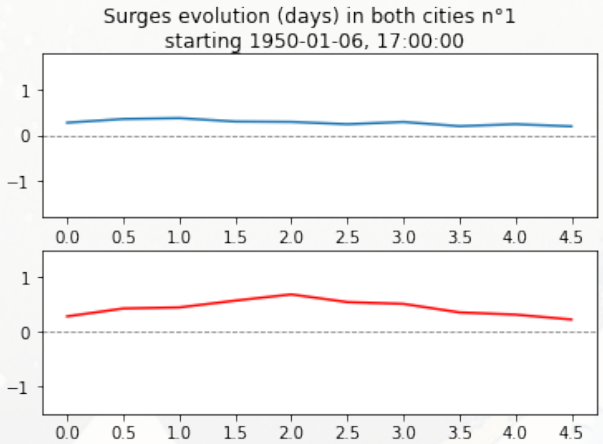



True surges




Benchmark prediction

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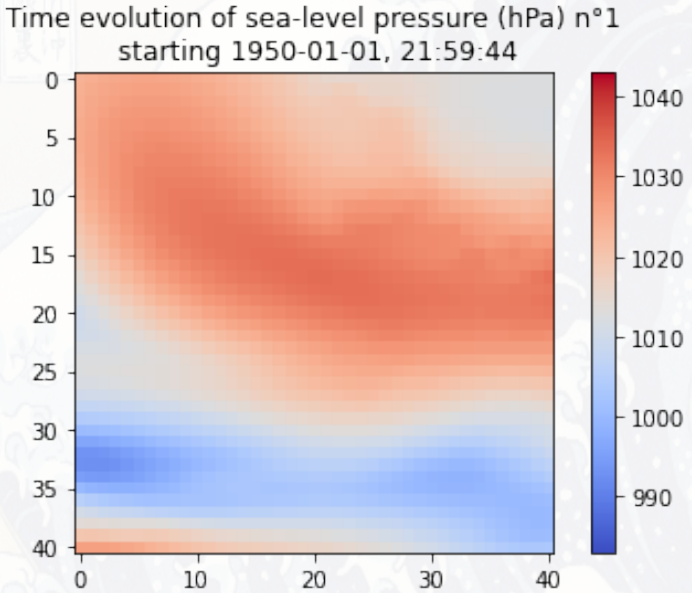
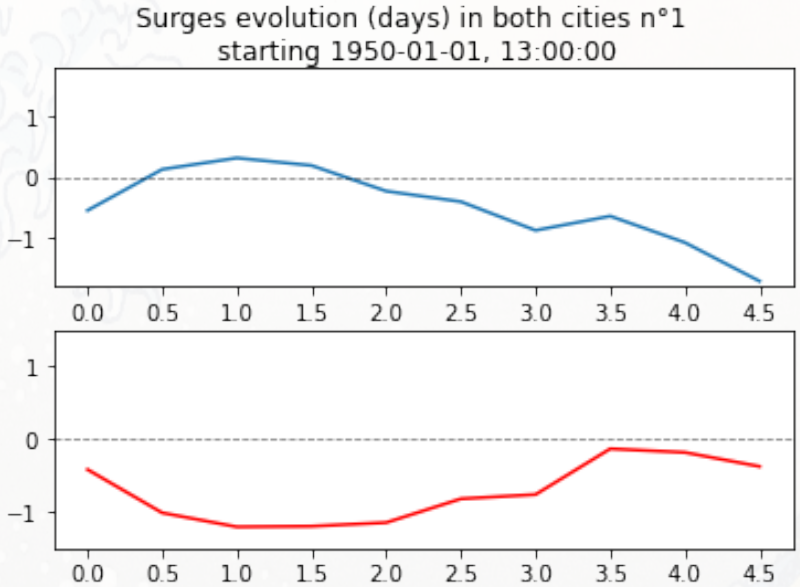
- $<$ 6% difference with the best solution online (0.4419).

# On an example



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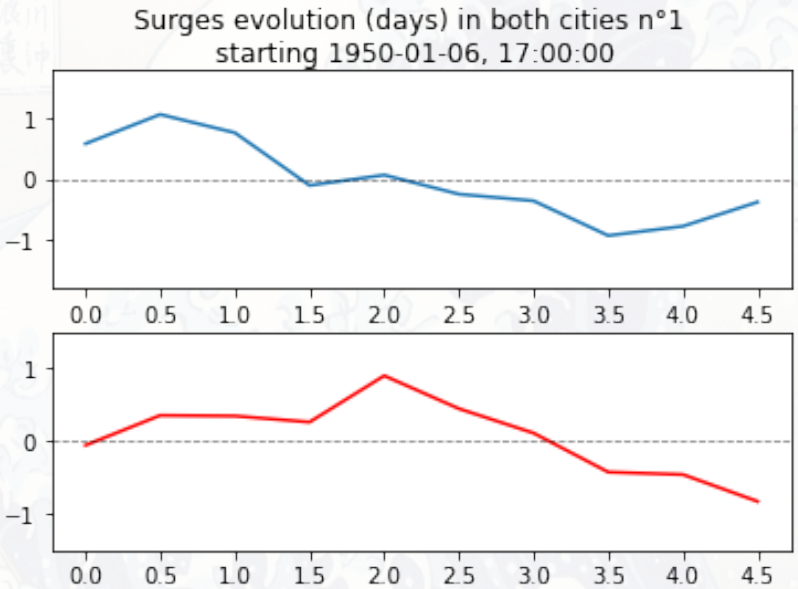


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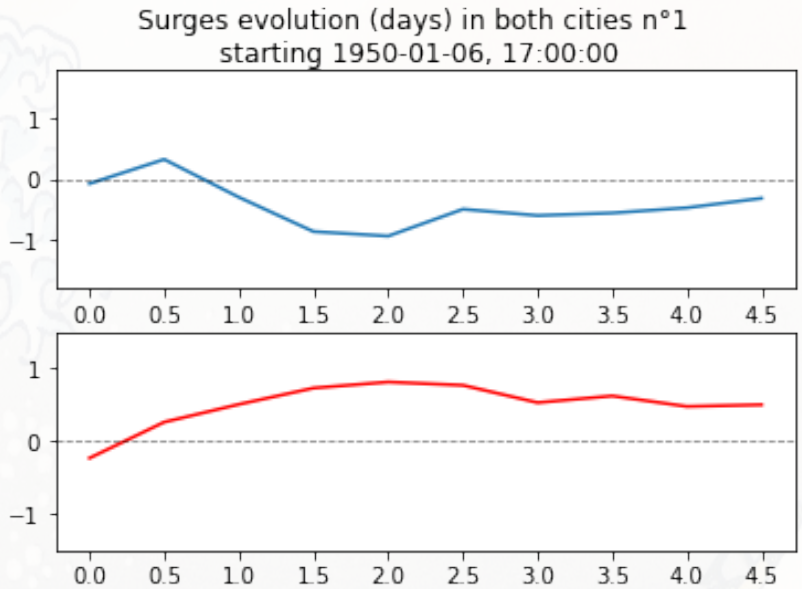


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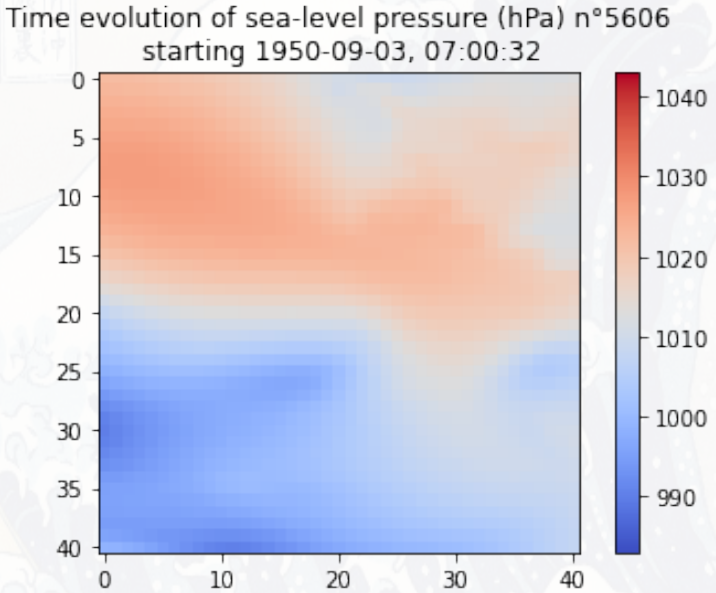
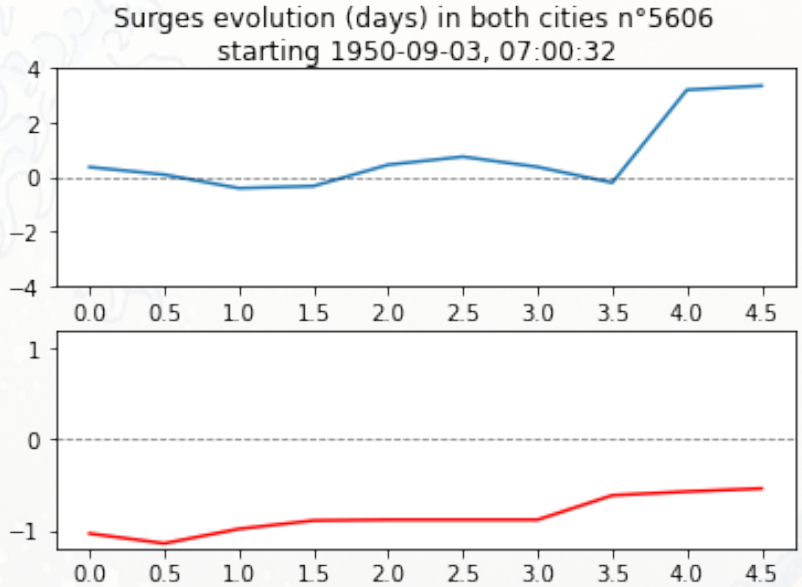
# Comparison to benchmark



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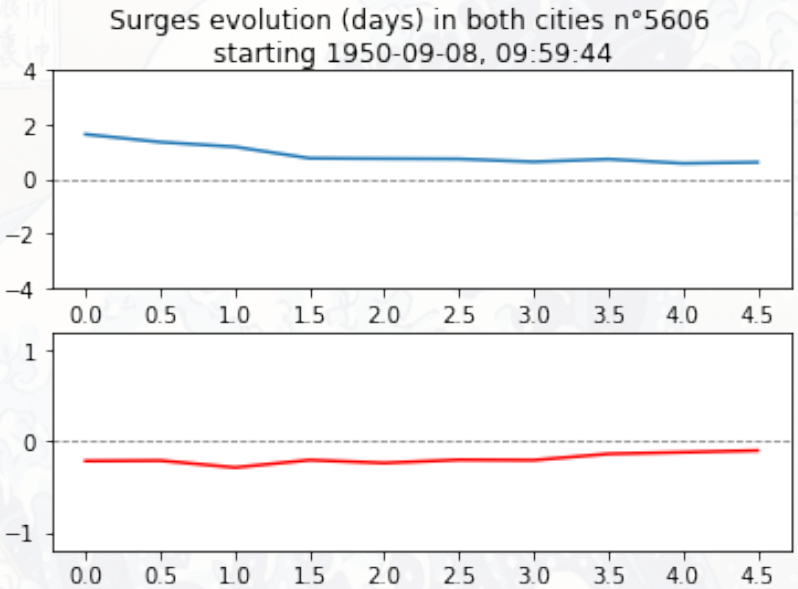


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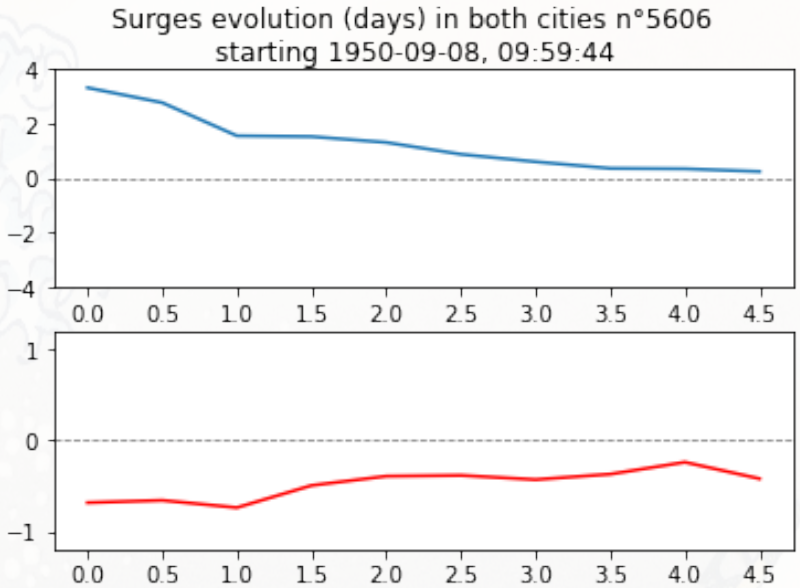


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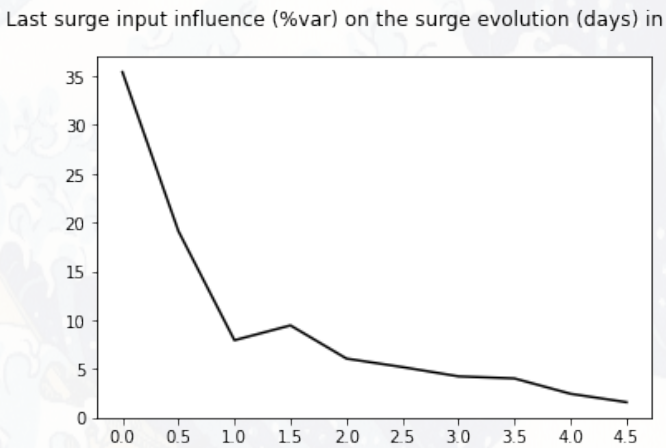


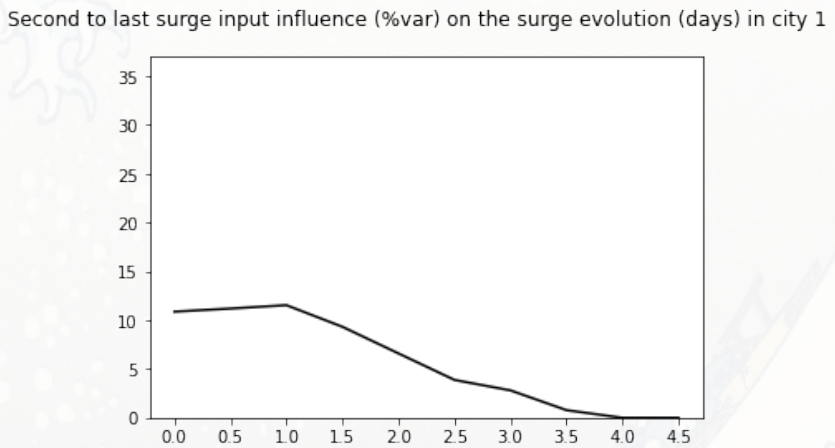

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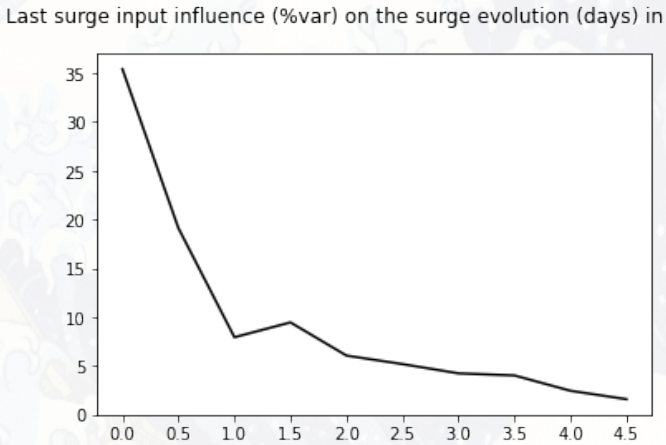


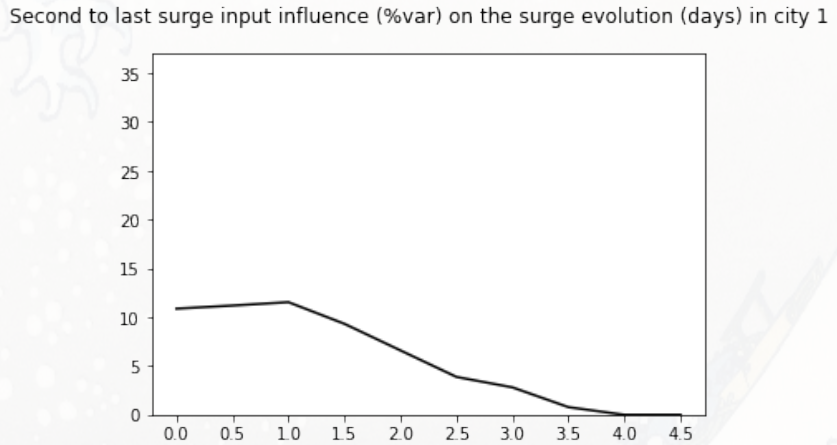


- Time: 6.6% (resp. 5.3%) variance increase every 10 years in city 1 (resp. 2). *Global warming?*

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- Neural Network instead of Lasso regression? Either overfits or behaves poorly compared to Lasso.

# Conclusion and further directions

- We have developped a simple method, using only PCA and Lasso regression, to predict sea surges.
- Explains $> 50\%$ of variance (benchmark 23%, best 56%).
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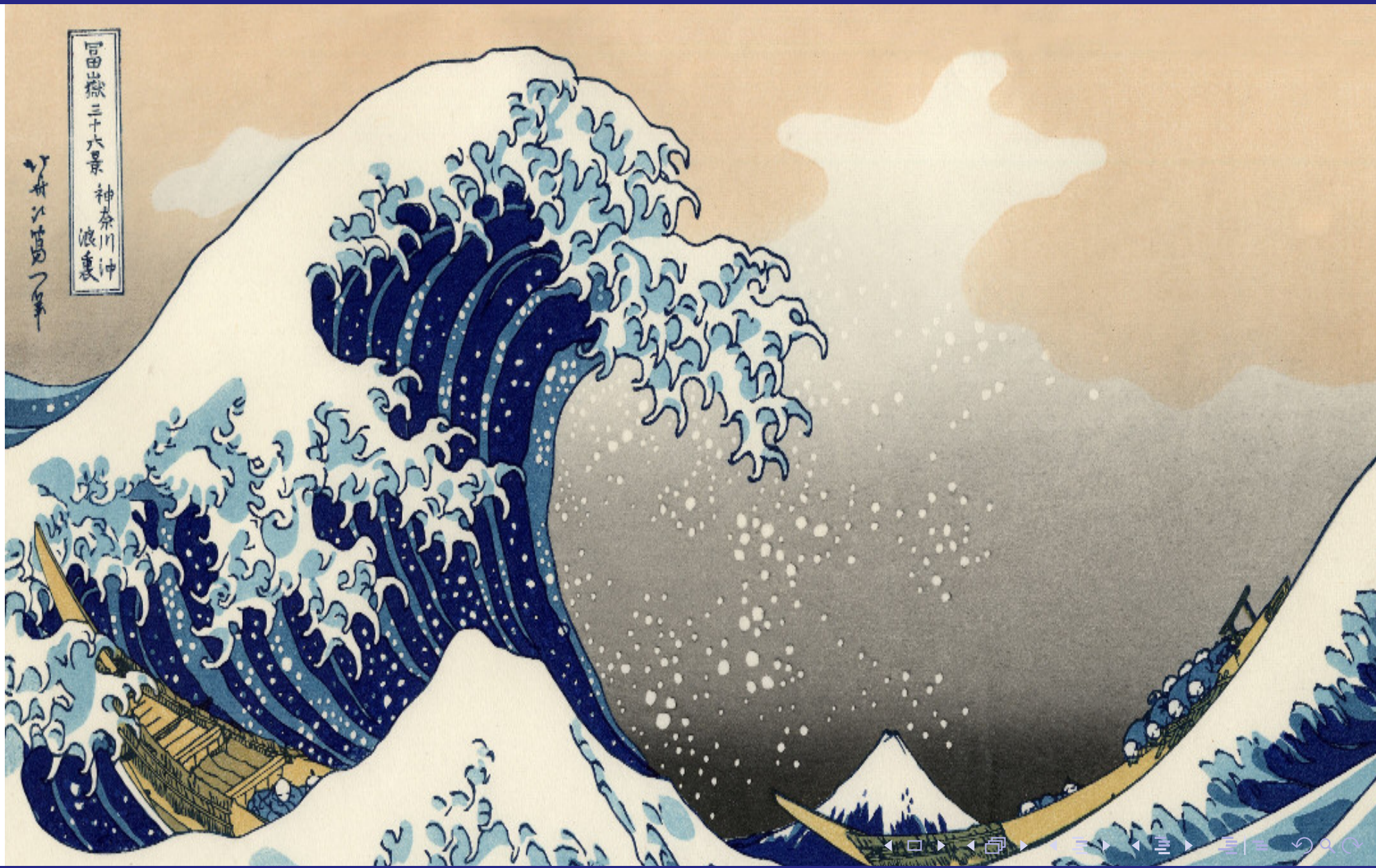
富嶽三十六景
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