Supporting Information for "Detection and attribution of climate change using a neural network"

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Introduction

This supporting information gives some details on the construction of the synthetic data. We present how the f_1, f_2 and f_3 time series are constructed. The methodology adopted for the choice of the hyperparameters for the neural network and the backward optimization is alsopresented.Then, the effect of the internal variability is investigated by repeating ROF and backward optimization using the HIST member from IPSL-CM6-LR the changes of the attributable anomalies are illustrated when accounting land use and ozone forcing in ROF. Lastly, we illustrate the reconstitution of the observation by the CNN.

Text S1. Synthetic dataset

We define three time series, f_1, f_2 and f_3 as $t \in \{1, 2, 3...115\}$:

$f_1 = 6.10^{-5}t^2 + 2.10^{-3}t$

$f_2 = -0.5sin(\frac{t\pi}{150})$

$f_3 = 1.10^{-5}t^2 - 1.10^{-3}t + f_{add}(t)$

f_{add} is a term added to represent the effect of three pseudo-volcanic eruptions for $t \in \{9, 49, 89\}$. This term is an additional anomaly that last for five years and is defined as :

$f_{add} = e^{\frac{2}{3}(t-t_j)}$ if $t \in [t_j, t_j + 4]$ and $t_j \in$ {9,49,89} and 0 otherwise

Text S2. Choice of hyper-parameters of the neural network

The hyperparameters of the CNN are the number of hidden layers, the cost function, the non-linear activation function, the size of the kernel, the length of the hidden layers, the learning rate, the type of padding used, and the batch size. The effects of the type of padding, the activation function, the batch size and the learning rate have not been investigated. We use the RMSE cost function and zero-values padding. A non-linear activation function is used between the hidden layers of the neural network in our case the hyperbolic tangent function. To determine the other hyper-parameters we use a cross validation. We considered the data from the 12 models but leaving out the data of one climate model. We train a CNN using the remaining models. The process was repeated by excluding successively each climate model. For each CNN built we also select randomly a historical member of the climate model left out as pseudo-observations, and perform the backward optimization. We compare the results to the ensemble mean of the simulations for this climate model. The mean value of the 12 backward optimization RMSE, is illustrated in Fig. S1 for different sets of hyperparameters.

The backward optimization RMSE are between 0.18°C and 0.41°C. The number of filters of the layer shows the largest influence, with a reduction of the RMSE for increasing length of the hidden layers. The number of hidden layers and the kernel sizes does not affect the RMSE.

We choose the architecture that gives the lowest backward optimization RMSE while keeping a small number of weights and biases with three hidden layers, a kernel sizes of 5 and number of filters of 32.

Text S3. Choice of the hyper-parameter of the backward optimization

Tables S1 and S2 shows the mean RMSE of the backward optimization described, for differents values of A, B, and C. The difference of performance is small in all experiments. We noted that large values of A and B reduce dramatically the variability of results of the backward optimization (not shown) and select A=0.05, B=0.01 and C=0.1. We choose a non-zero value for B to keep a background term although it only has a marginal effect on the RMSE.

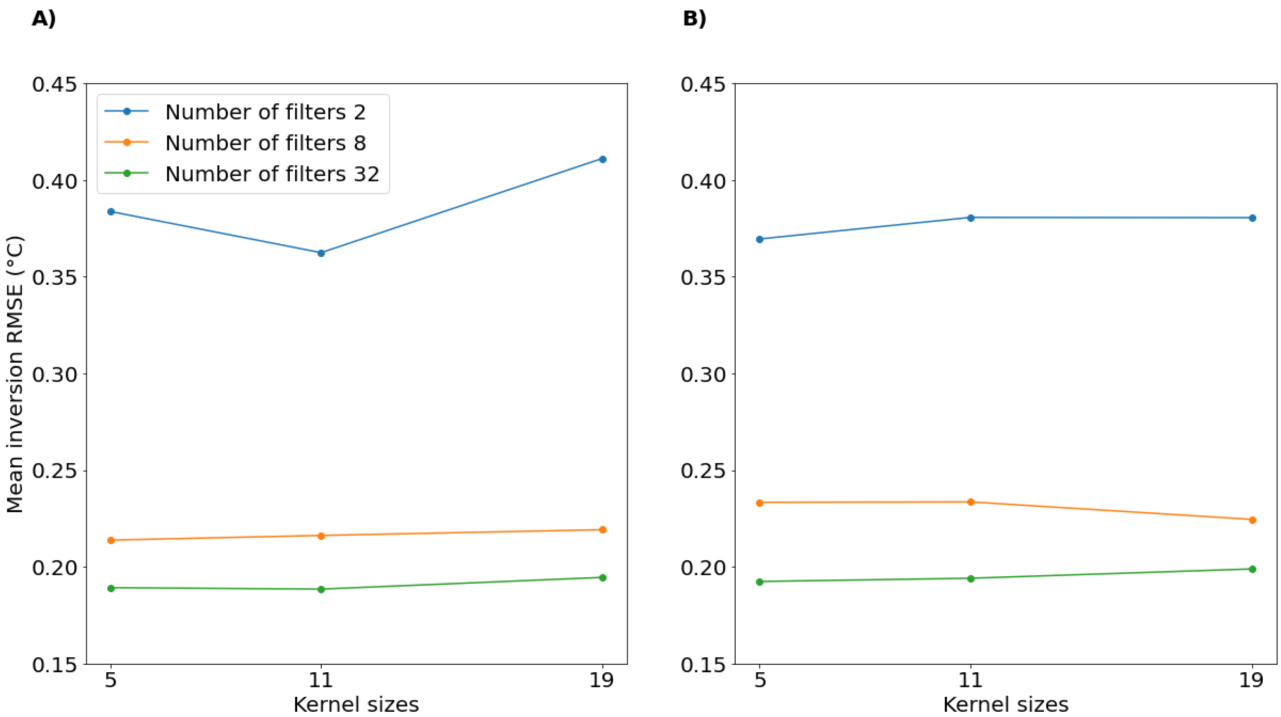

Figure S1. A) Mean cross-validation RMSE (in °C) for differents kernel sizes and number of filters while using three hidden layers. B) same as A) but with 5 hidden layers.

Table S1. Mean cross-validation RMSE (in °C) of the backward optimization for different values of A and B, while C is fixed to 0.1.

	A=0.01	A=0.05	A=0.1
B=0	0.205	0.190	0.189
B=0.01	0.199	0.189	0.190
B=0.1	0.191	0.191	0.192

Table S2. Mean cross-validation RMSE (in °C) of the backward optimization for different values of B and C, while A is fixed to 0.05°C.

	C=0	C=0.01	C=0.1
B=0	0.188	0.187	0.188
B=0.01	0.190	0.188	0.189
B=0.1	0.191	0.191	0.191

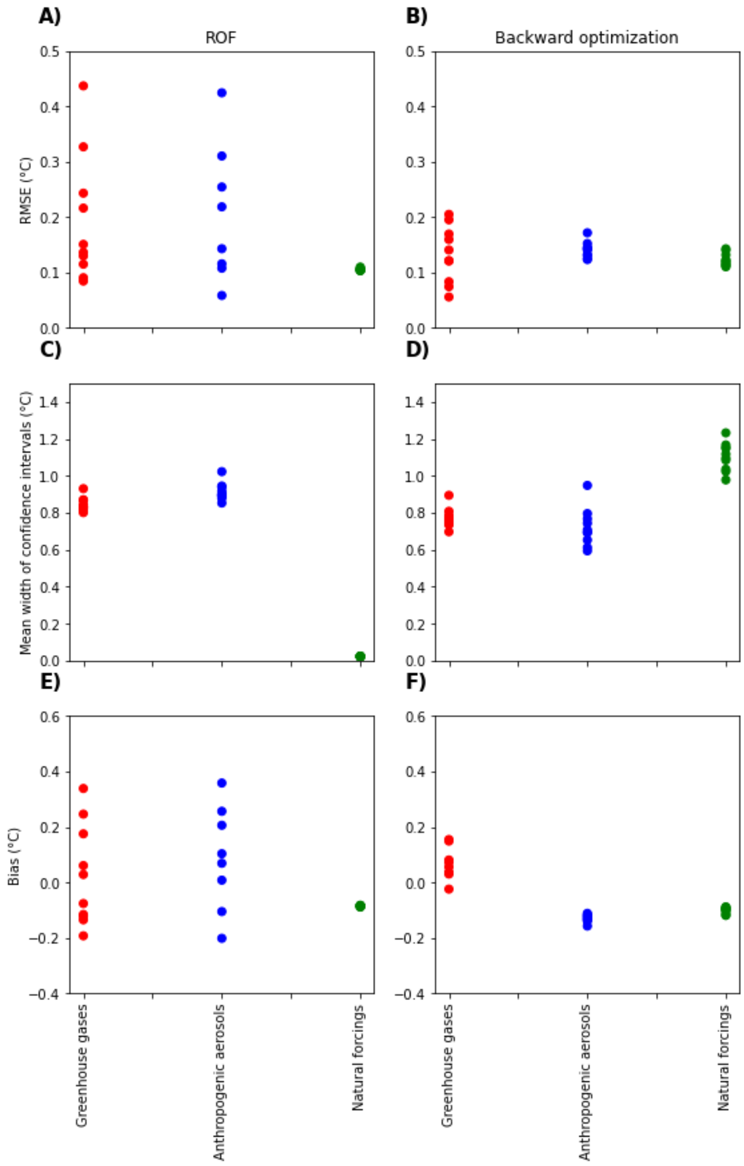

Figure S2. Performances of attribution methodologies on the 10 removed IPSL-CM6-LR members A) RMSE distribution when using ROF and all 10 removed members as pseudo-observation for the attributable GSAT anomaly of (red) greenhouse gases, (blue) anthropogenic aerosols, (green) natural forcing. B) Same as A) for the backward optimization. C) Distribution of the widths of the 90 % percent confidence intervals in 2000-2014 when using ROF. D) same as C) but for backward optimization E) Distribution of the time mean differences between the estimated and ensemble mean GSAT attribuable to the forcings when using ROF. F) Same as E) for backward optimization.

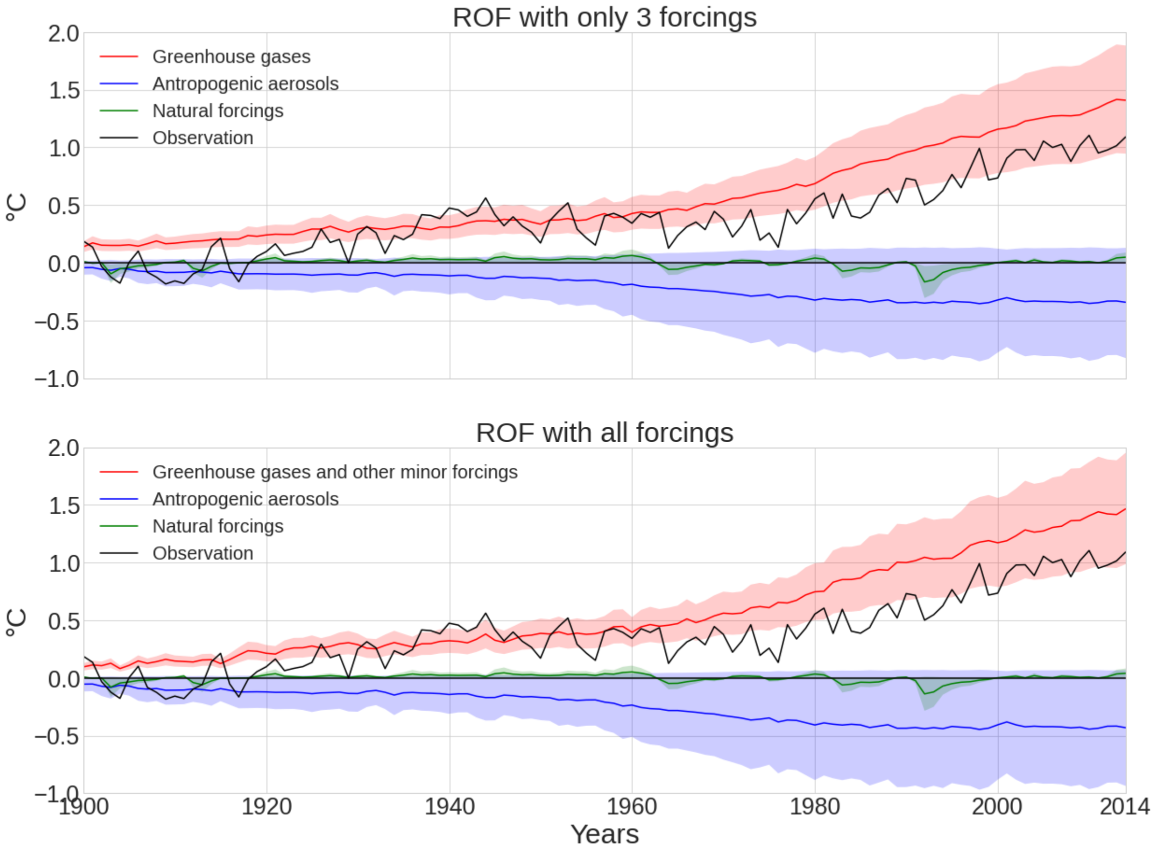

Figure S3. Attributable GSAT anomalies calculated from ROF with observations when using anthropogenic aerosols, natural forcing and greenhouse gases as forcings (top) anthropogenic aerosols, natural forcing and greenhouse gases and other anthropogenic effect combined (bottom).

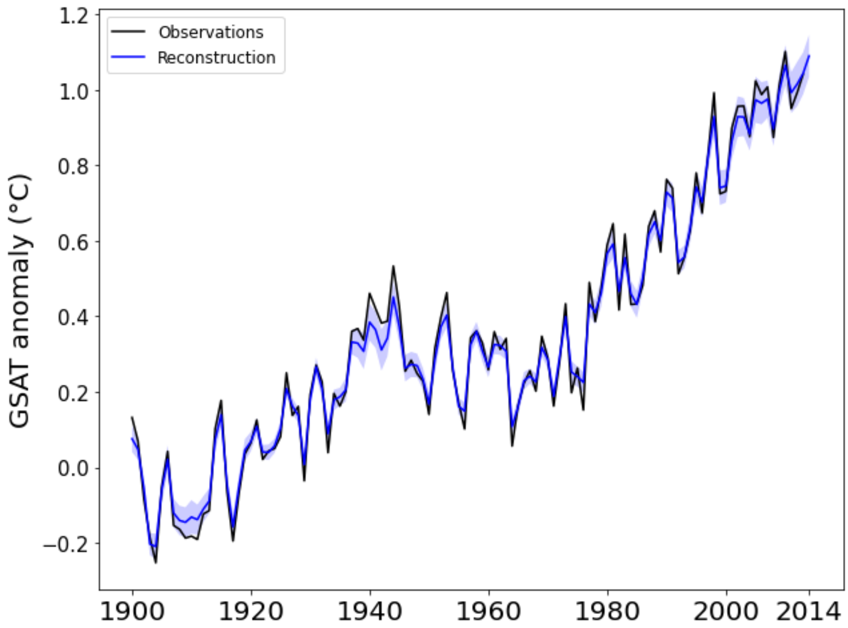

Figure S4. (Black) Observed GSAT anomalies, in °C, and (blue) the mean reconstruction of the observation by the CNN. Color shade shows the 90% percents confidence intervals of the mean reconstruction obtained across the 1200 backward optimization results available.