Neural network models for climate, and pollution in the Arctic

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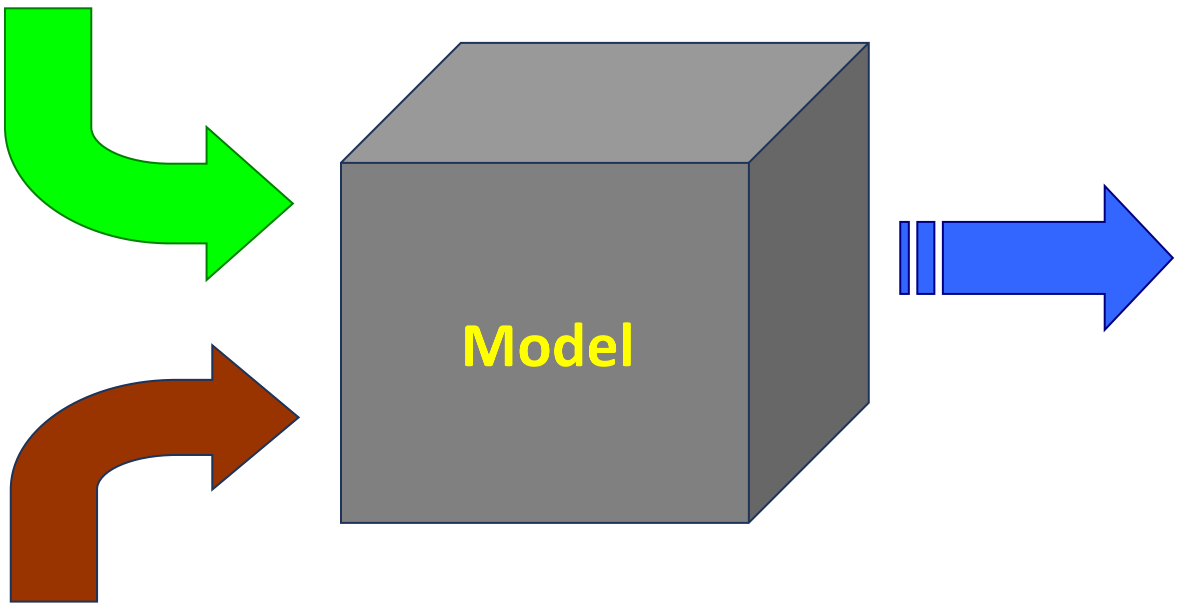
Attribution

Dynamical models: Global Climate Models (GCMs)

Natural inputs

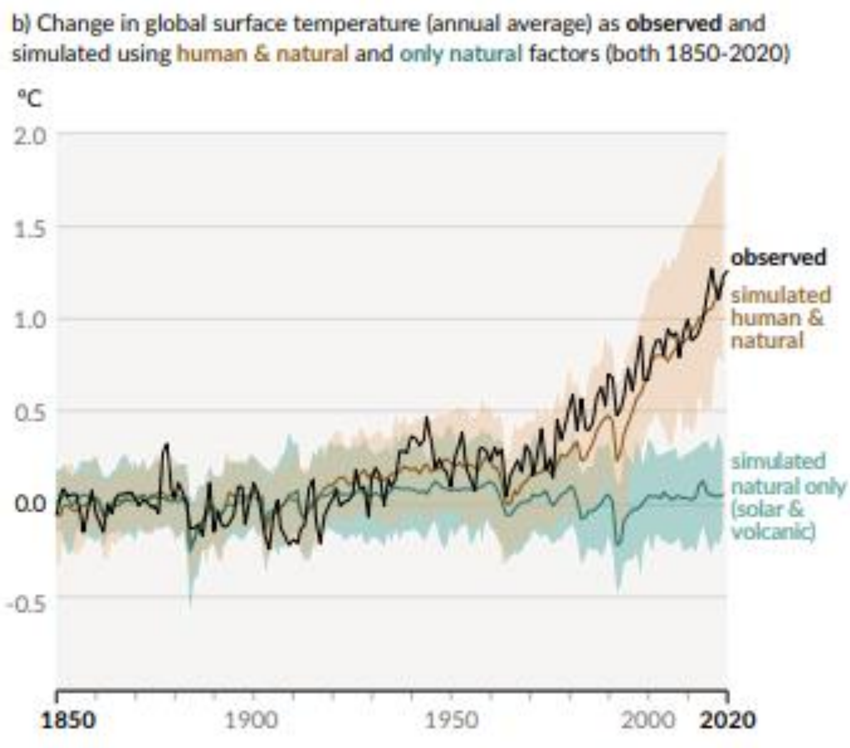


Climate behaviour

Anthropogenic inputs

Attribution

Dynamical models: Global Climate Models (GCMs)



Beige line:

We give the model all the actually observed values of external influences (forcings)

Blue line:

Anthropogenic forcings are held fixed at constant 1850 values

IPCC, 2021

From dynamical modelling…

However, the results of GCMs could crucially depend on the uncertainties in our theoretical knowledge of processes and feedbacks → doubtful results?

At present, there are systems which learn directly from data, without any reference to previous knowledge. Can we apply them to our attribution problem?

An independent (more "holystic") analysis could be interesting.

… to a different strategy

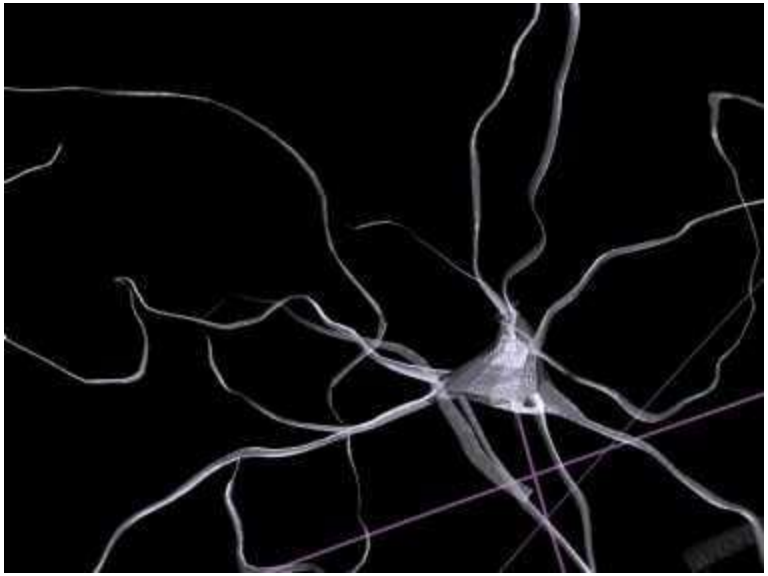
A child who learns to walk.

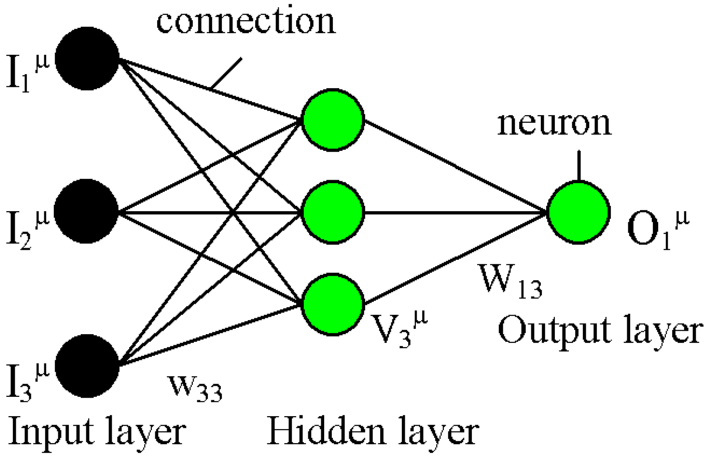
Trials and errors.

Initially he hits against tables and chairs.

He learns the rules for moving in a room when he adjusts his own synapses (the “links” between neurons).

A different strategy



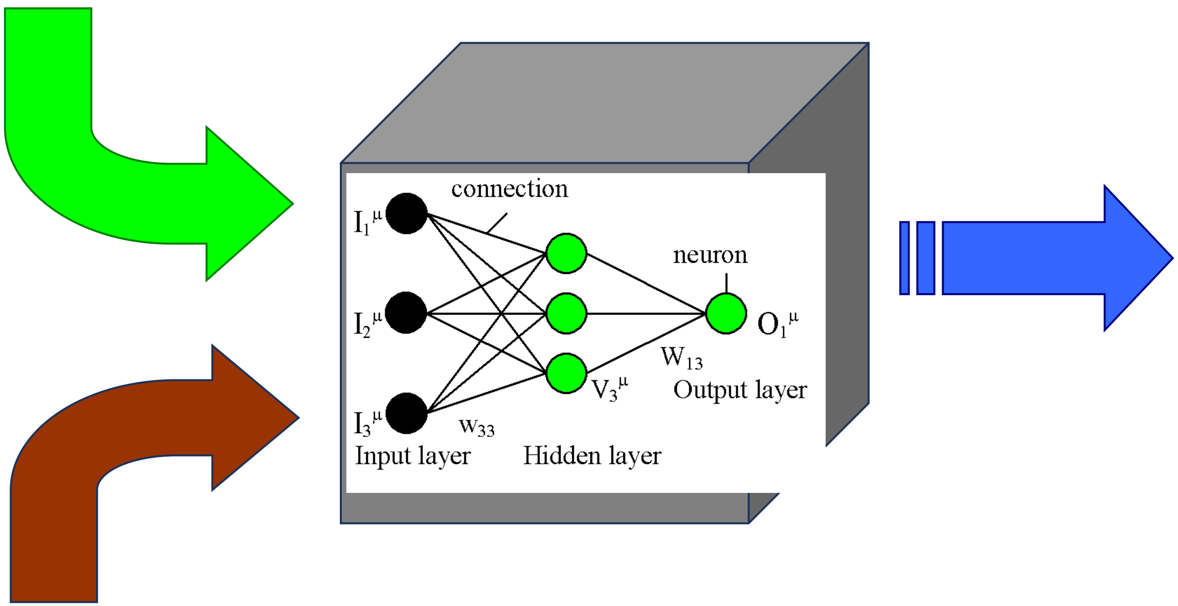


Can a little artificial brain, a neural network, learn the rules of evolution of global temperature on the Earth, without any previous knowledge?

Forcings as predictors (inputs) and temperature as predictand (target).

A neural network model

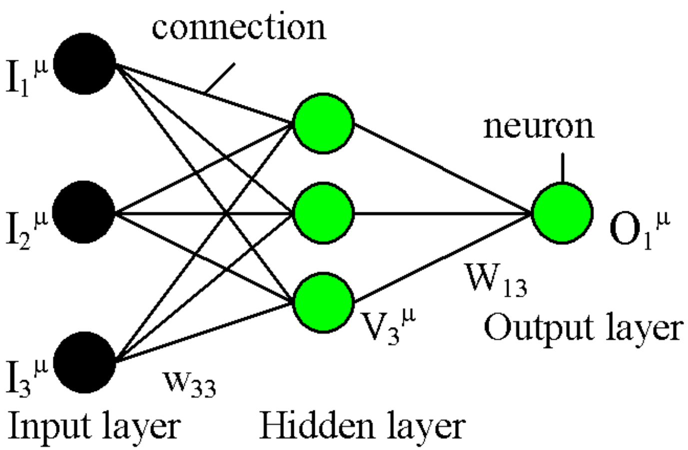
Natural inputs



Climate behaviour

Anthropogenic inputs

The neural network tool



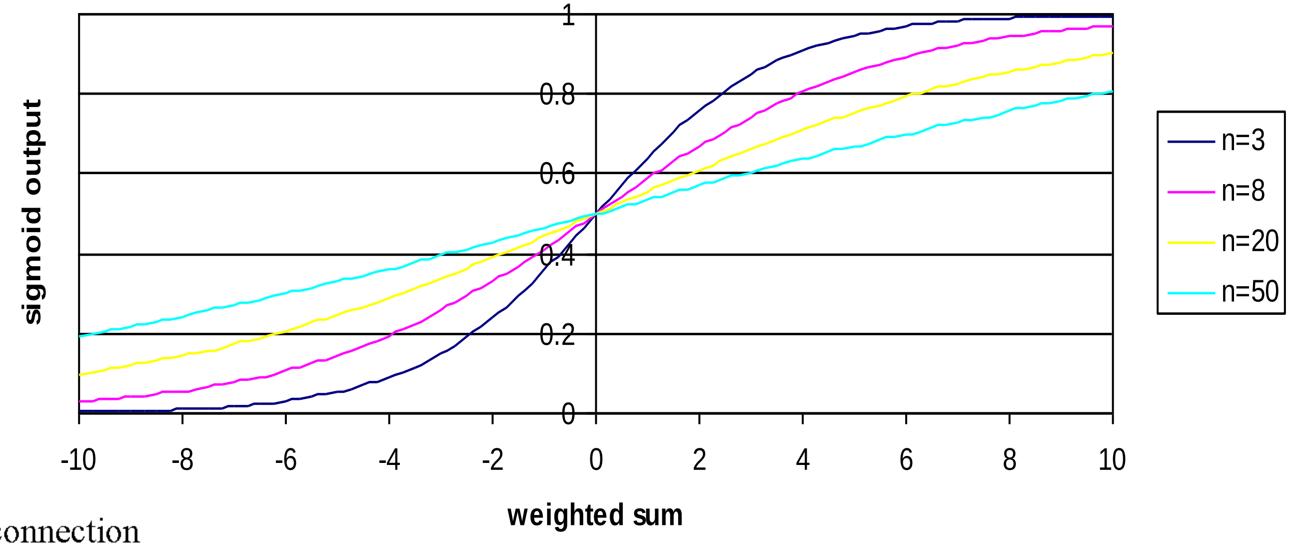
Quite standard Multi-Layer Perceptrons (MLPs):

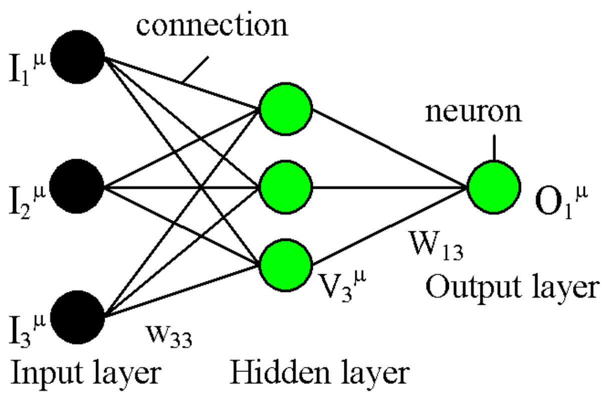
- feed-forward networks with one hidden layer;
- quasi-Newtonian back-propagation method: Broyden-Fletcher-Golfarb-Shanno (BFGS) algorithm (new).

A specific tool for short historical data sets:

- ensemble leave-one-out with early stopping (see Pasini, 2015; Pasini & Amendola, 2024).

The neural network tool



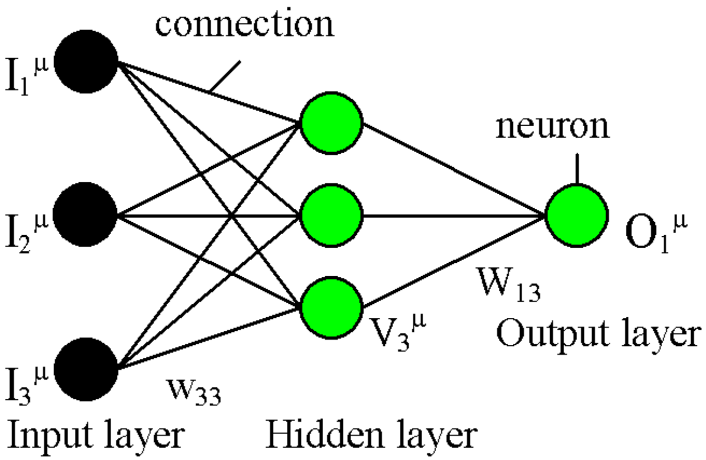


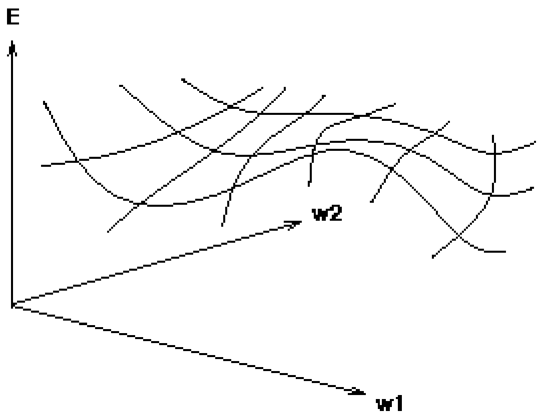
$$g_j\left(h_j^\mu\right)=\frac{1}{1+\exp\left(-\beta h_j^\mu\right)}$$

The neural network tool

$$O_i^\mu = f_i\left(\sum_j W_{ij} g_j\left(\sum_k w_{jk} I_k^\mu\right)\right)$$

$$E^\mu = \frac{1}{2}\sum_i \left(T_i^\mu - O_i^\mu\right)^2$$

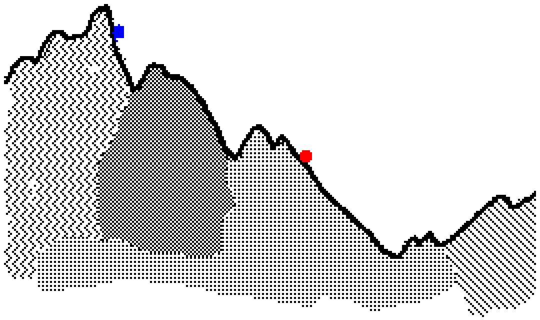




The neural network tool

$$W_{ij}(t+1) = W_{ij}(t) - \eta \frac{\partial E^{\mu}}{\partial W_{ij}(t)} + m\left[W_{ij}(t) - W_{ij}(t-1)\right] =$$

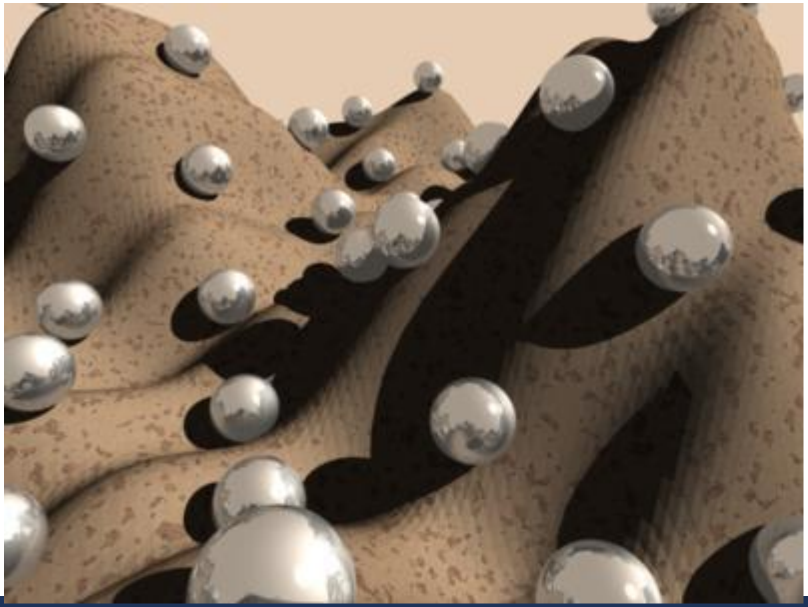
$$= W_{ij}(t) + \eta \; f_i'\left(h_i^{\mu}\right)\left(T_i^{\mu} - O_i^{\mu}\right)V_j^{\mu} + m\left[W_{ij}(t) - W_{ij}(t-1)\right]$$



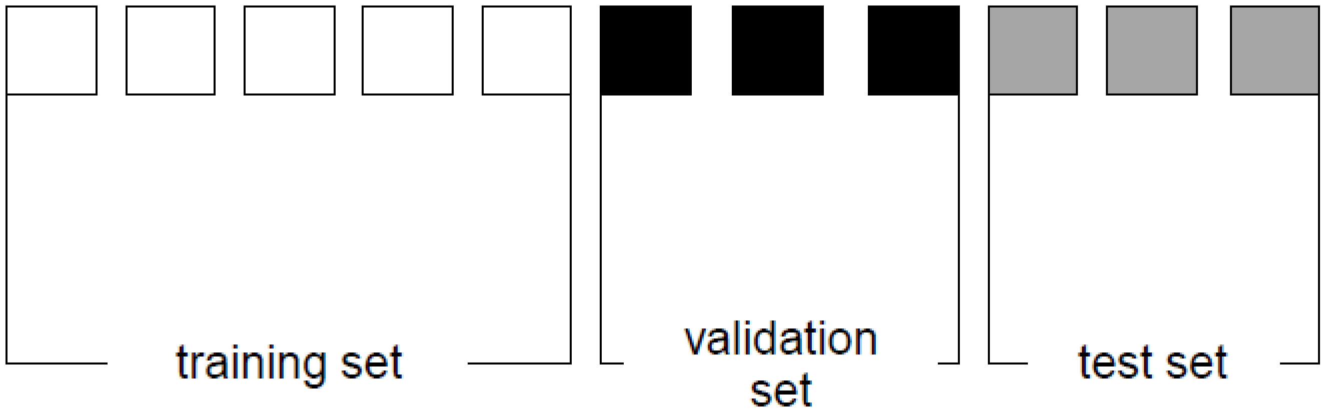
The neural network tool

$$w_{jk}(t+1) = w_{jk}(t) - \eta \frac{\partial E^{\mu}}{\partial w_{jk}(t)} + m\left[w_{jk}(t) - w_{jk}(t-1)\right] =$$

$$= w_{jk}(t) + \eta \sum_{i} \left(T_i^{\mu} - O_i^{\mu}\right) f'_i\left(h_i^{\mu}\right) W_{ij} g'_j\left(h_j^{\mu}\right) I_k^{\mu} + m\left[w_{jk}(t) - w_{jk}(t-1)\right]$$

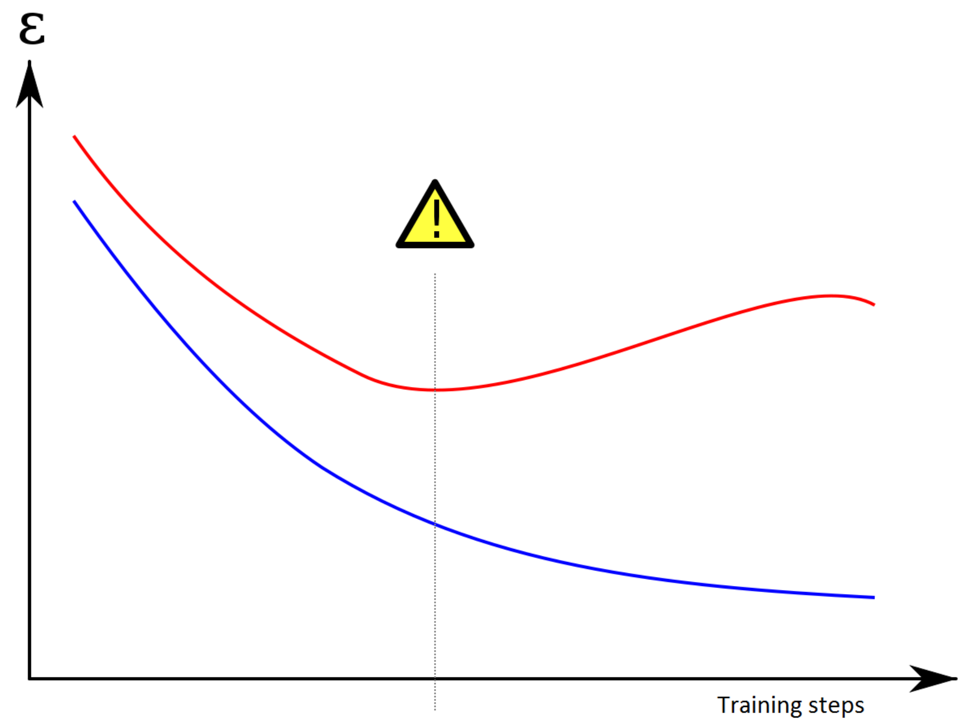


Training



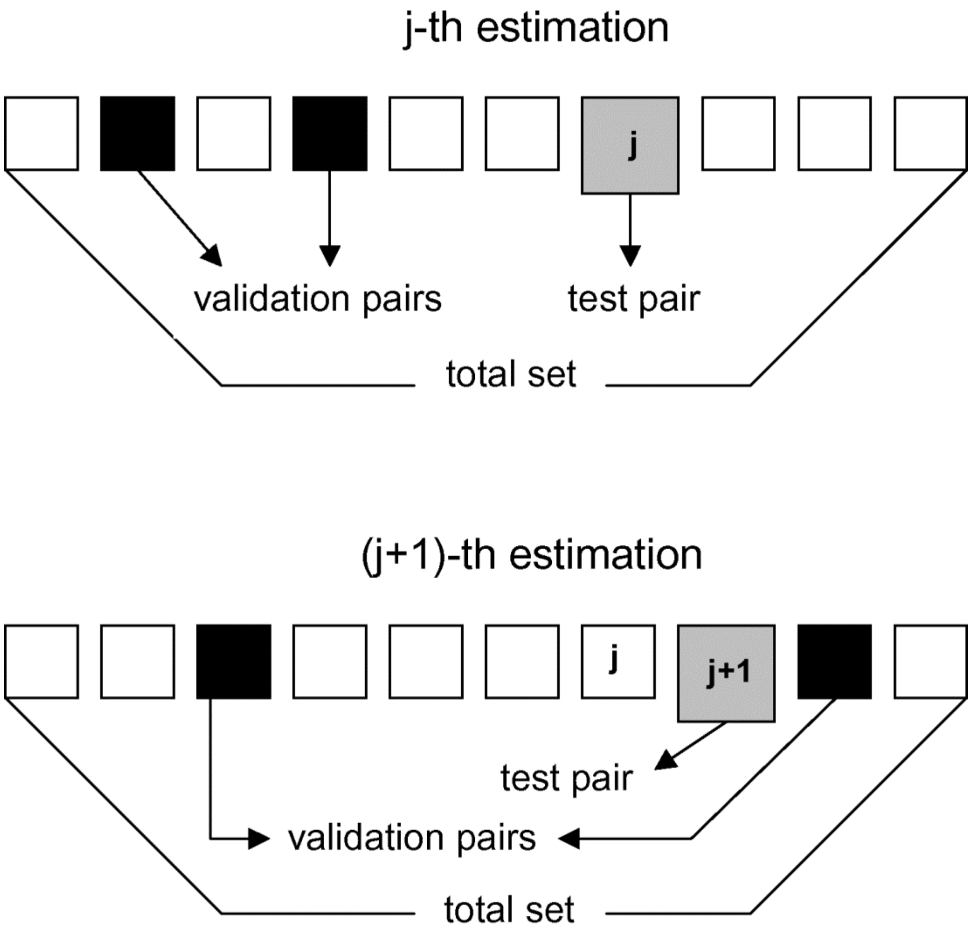
The weights are set by operating iteratively on the traning set, but the iterations only stop when...

Training and stopping



… the error begins to increase on the validation set (early stopping).

Training for small datasets



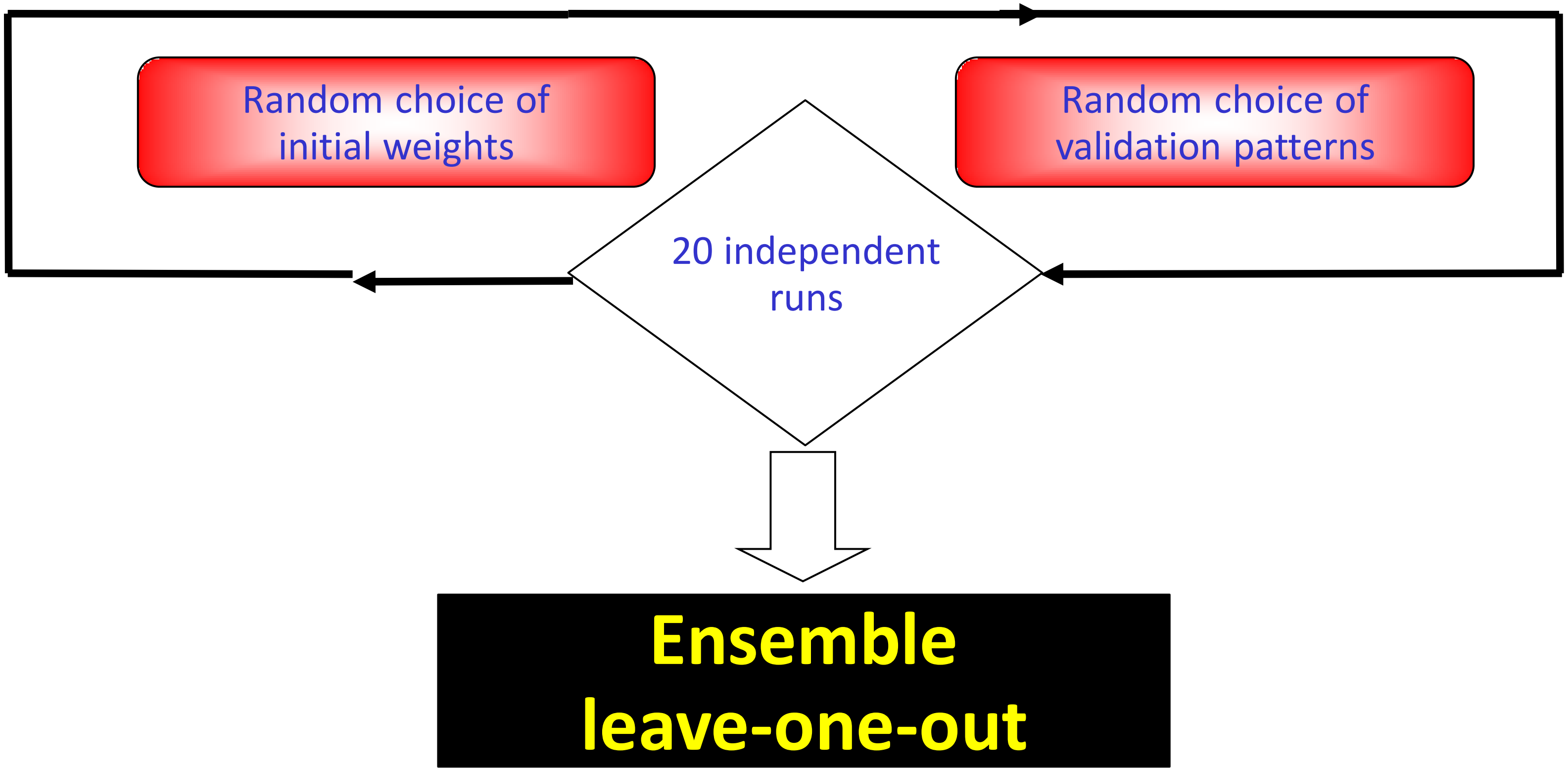
About 170 inputs-target pairs.

Generalized "leave-one-out" procedure.

Iterations stop when the error on the validation set begins to increase.

We perform ensemble runs, one for each choice of the initial weights and the elements of the validation set.

Training for small datasets



Neural reconstructions

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Attribution of recent temperature behaviour reassessed by a neural-network method

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Antonello Pasini[1], Paolo Racca[2], Stefano Amendola[3], Giorgio Cartocci[3] & Claudio Cassardo[4,5]

Attribution studies on recent global warming by Global Climate Model (GCM) ensembles converge in showing the fundamental role of anthropogenic forcings as primary drivers of temperature in the last half century. However, despite their differences, all these models pertain to the same dynamical approach and come from a common ancestor, so that their very similar results in attribution studies are not surprising and cannot be considered as a clear proof of robustness of the results themselves. Thus, here we adopt a completely different, non-dynamical, data-driven and fully nonlinear approach to the attribution problem. By means of neural network (NN) modelling, and analysing the last 160 years, we perform attribution experiments and find that the strong increase in global temperature of the last half century may be attributed basically to anthropogenic forcings (with details on their specific contributions), while the Sun considerably influences the period 1910–1975. Furthermore, the role of sulphate aerosols and Atlantic Multidecadal Oscillation for better catching interannual to decadal temperature variability is clarified. Sensitivity analyses to forcing changes are also performed. The NN outcomes both corroborate our previous knowledge from GCMs and give new insight into the relative contributions of external forcings and internal variability to climate.

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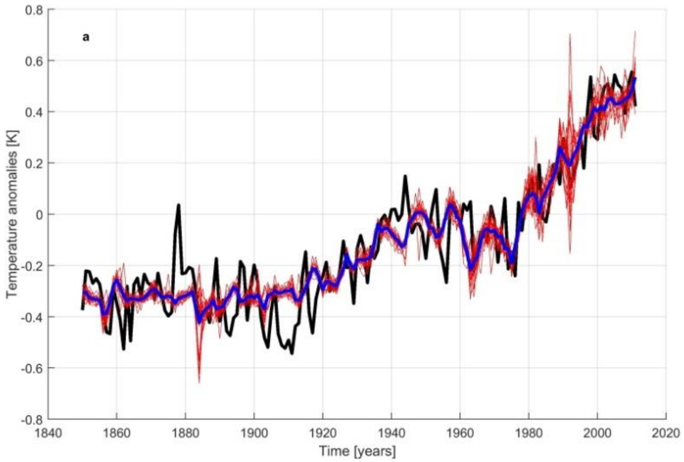
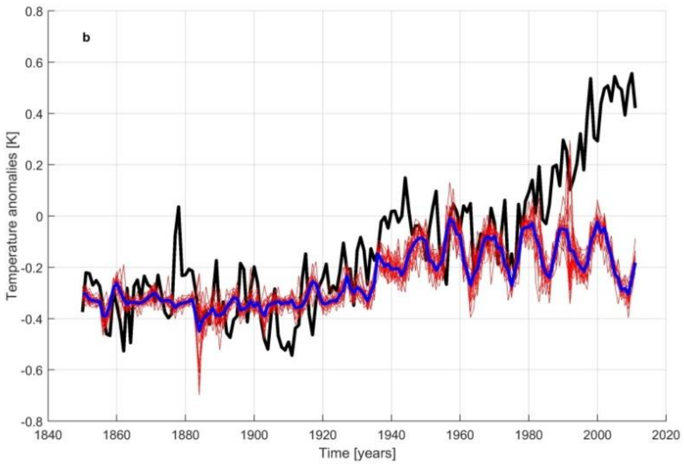
Neural reconstructions



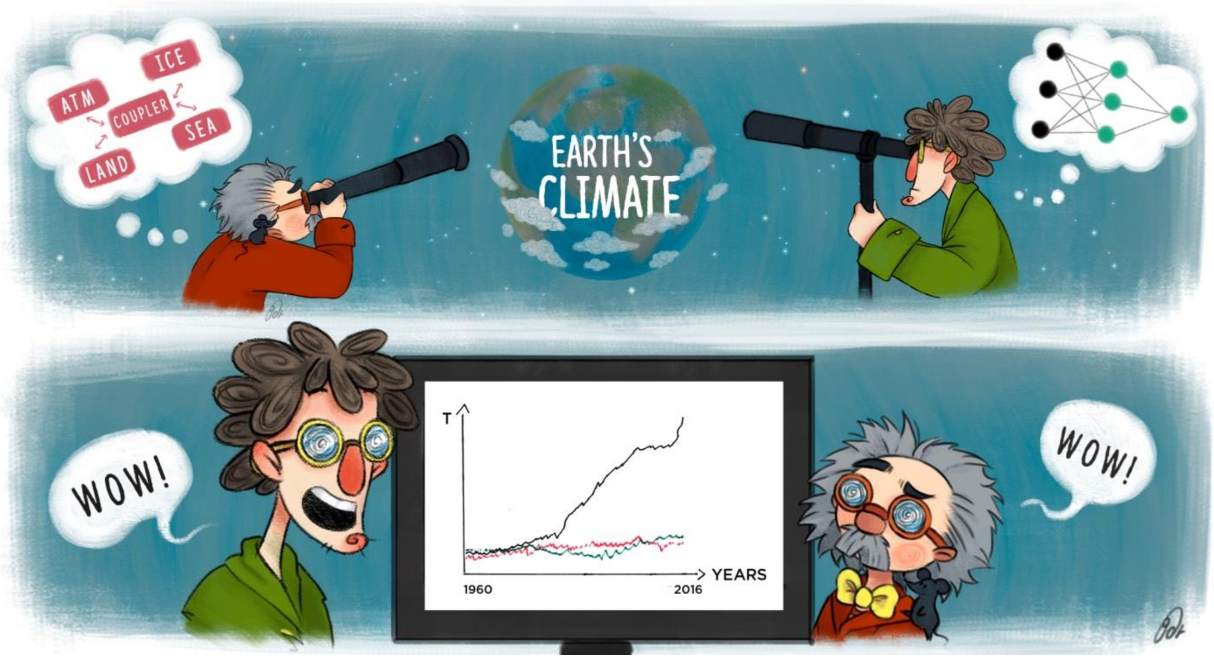
With real natural and anthropogenic forcings

Pasini et al., 2017



With anthropogenic forcings fixed at their values of 1850

Robustness


ICE
ATM
COUPLER
SEA
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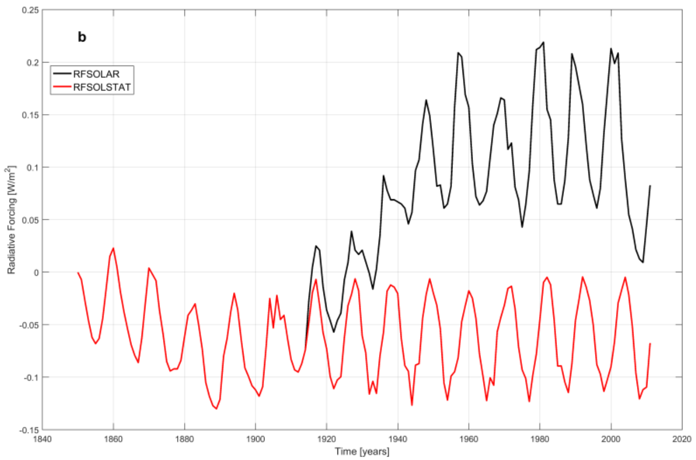
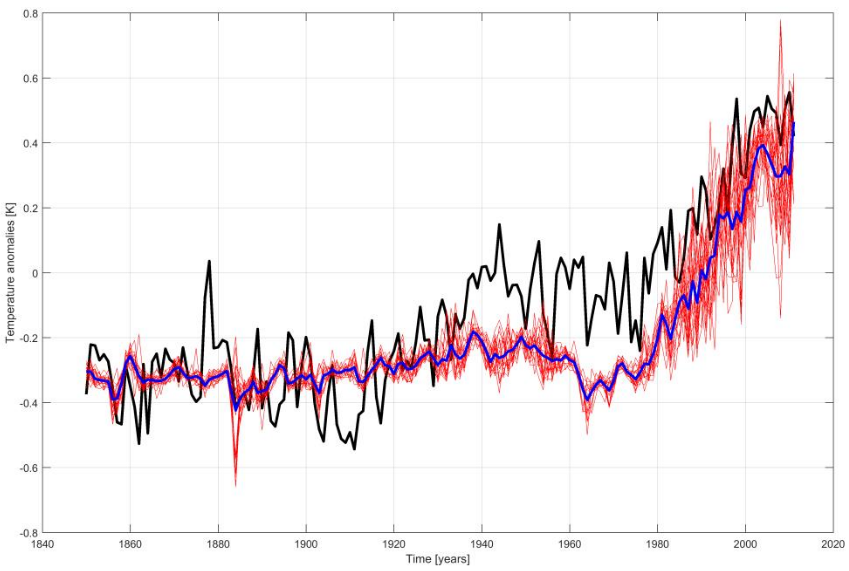
EARTH'S
CLIMATE
WOW!
T
YEARS
1960
2016
WOW!

Neural reconstructions (T)



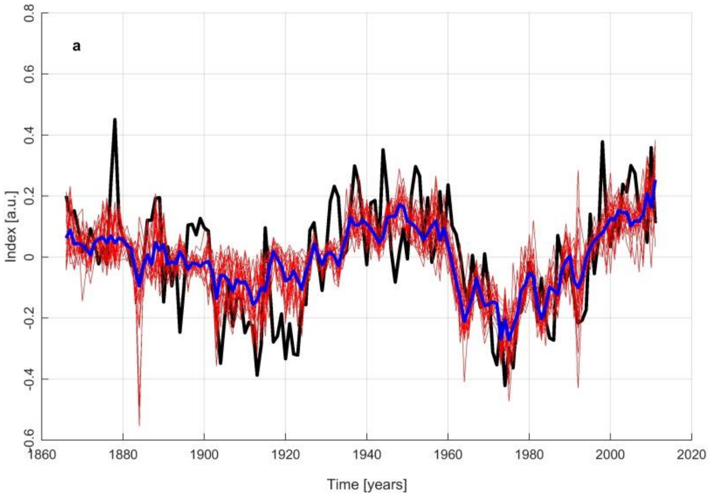
Real and stationary solar forcing

Pasini et al., 2017



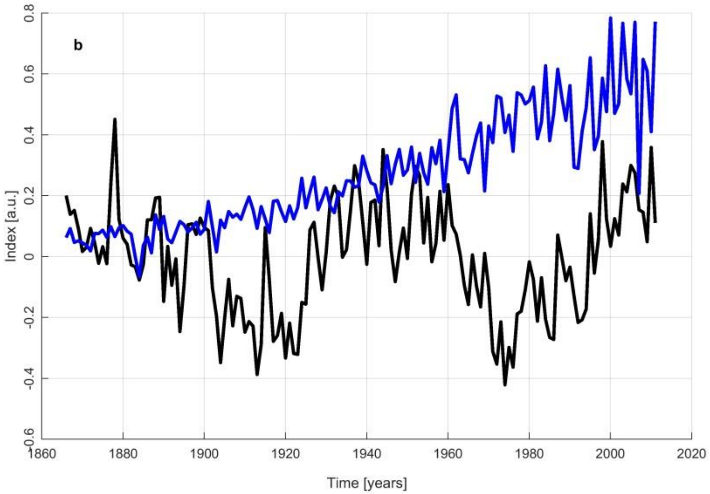
With stationary solar forcing

Neural reconstructions (AMO)



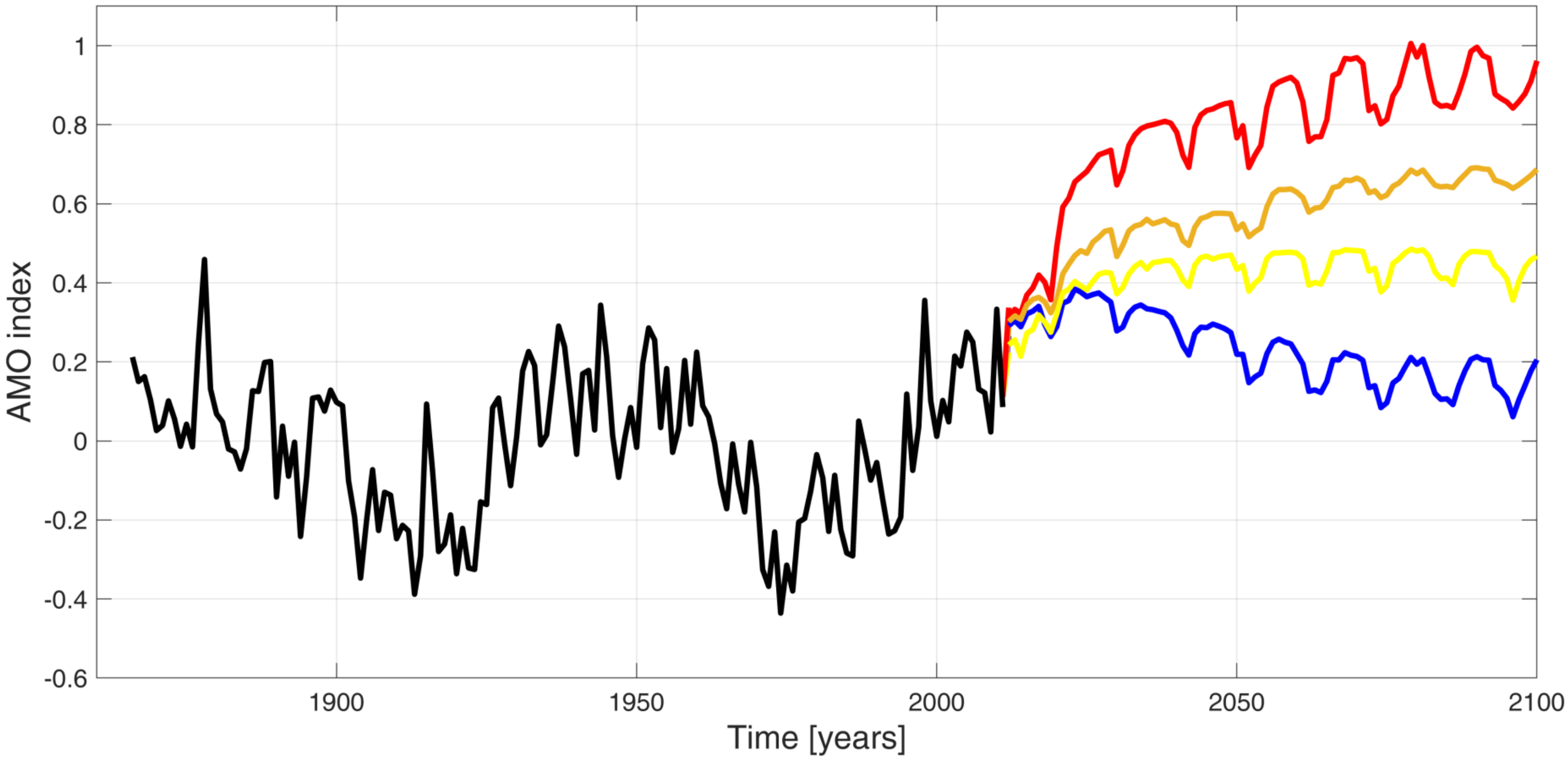
With the real values of all the forcings

Pasini et al., 2017



With the sulphate forcing kept constant at its value of 1866

Neural predictions (AMO)



Pasini & Amendola, 2022

A time series approach to attribution

The future global temperature T can be predicted from its past values:

$$T_t = f_1(T_{t-1}, T_{t-2}, \ldots)$$

Then you can see if the forecast improves by adding past values of another variable x, e.g. the greenhouse gas trend, or the influence of the Sun:

$$T_t = f_2(T_{t-1}, T_{t-2}, \ldots, x_{t-1}, x_{t-2}, \ldots)$$

If this happens, it means that the past values of x have some influence on the values of T, i.e. they "cause" it in some way...

Granger causality

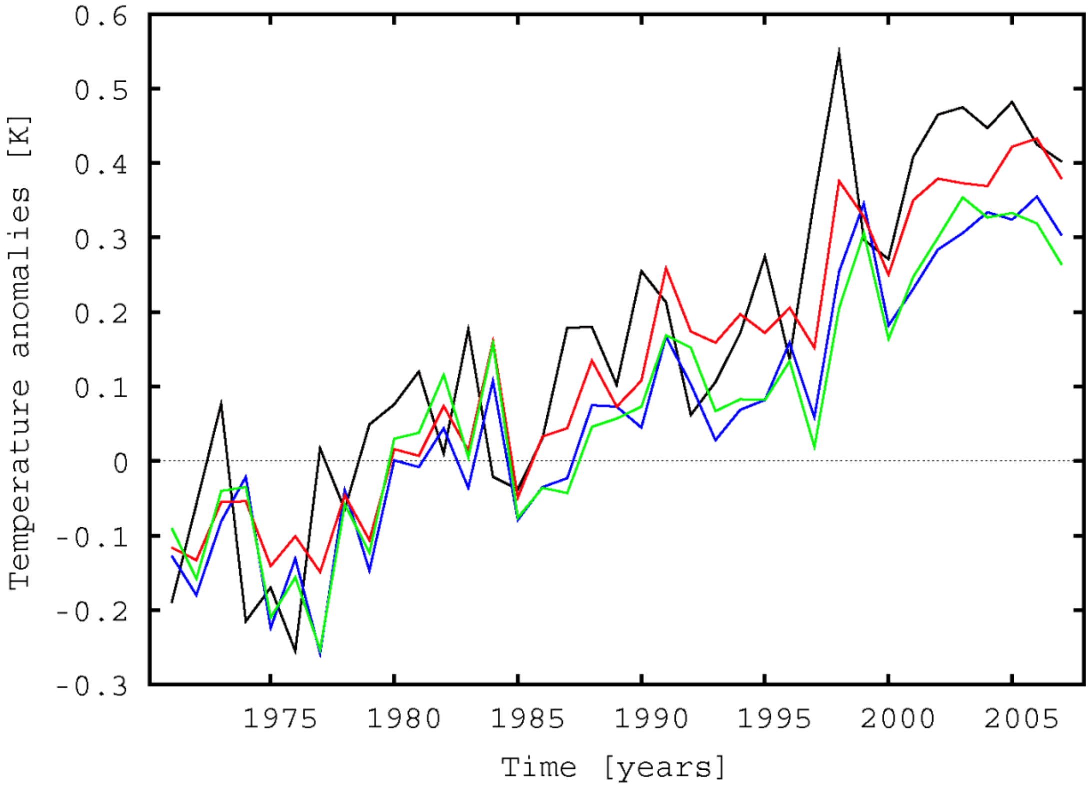
In general, we say that a variable x causes (in Granger's sense) another variable y if the future values of y can be better predicted using the past values of x and y than using only the past values of y.

AR: $$y_t = \delta_2 + \sum_{j=1}^{k} \gamma_j y_{t-j} + u_t$$

VAR: $$y_t = \delta_1^{(i)} + \sum_{j=1}^{k} \alpha_j^{(i)} y_{t-j} + \sum_{j=1}^{k} \beta_j^{(i)} x_{i,t-j} + v_t^{(i)}$$

For us, y=T and x_i=external forcing

Granger causality



Black: temperature

Blue: AR forecast

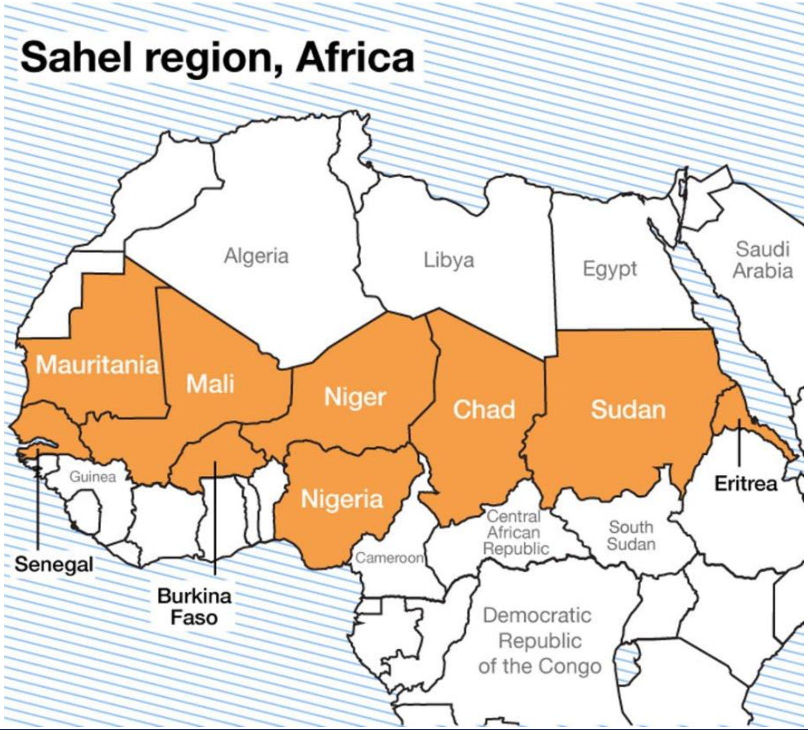
Green: VAR forecast with x = solar rad.

Red: VAR forecast with x = radiative forcing of greenhouse gases

Attanasio, Pasini, Triacca (2012)

Climate-induced migrations

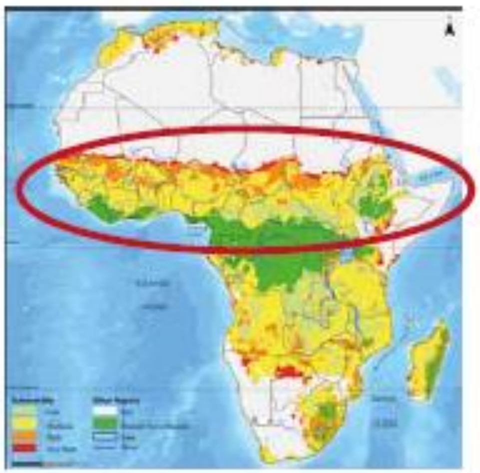
Here, we focus on a very critical and fragile zone: the Sahelian band:



Climate-induced migrations

Sahel is critical from many points of view:

Desertification vulnerability in Africa (2008)



Conflicts and food riots in Africa 2007-2008

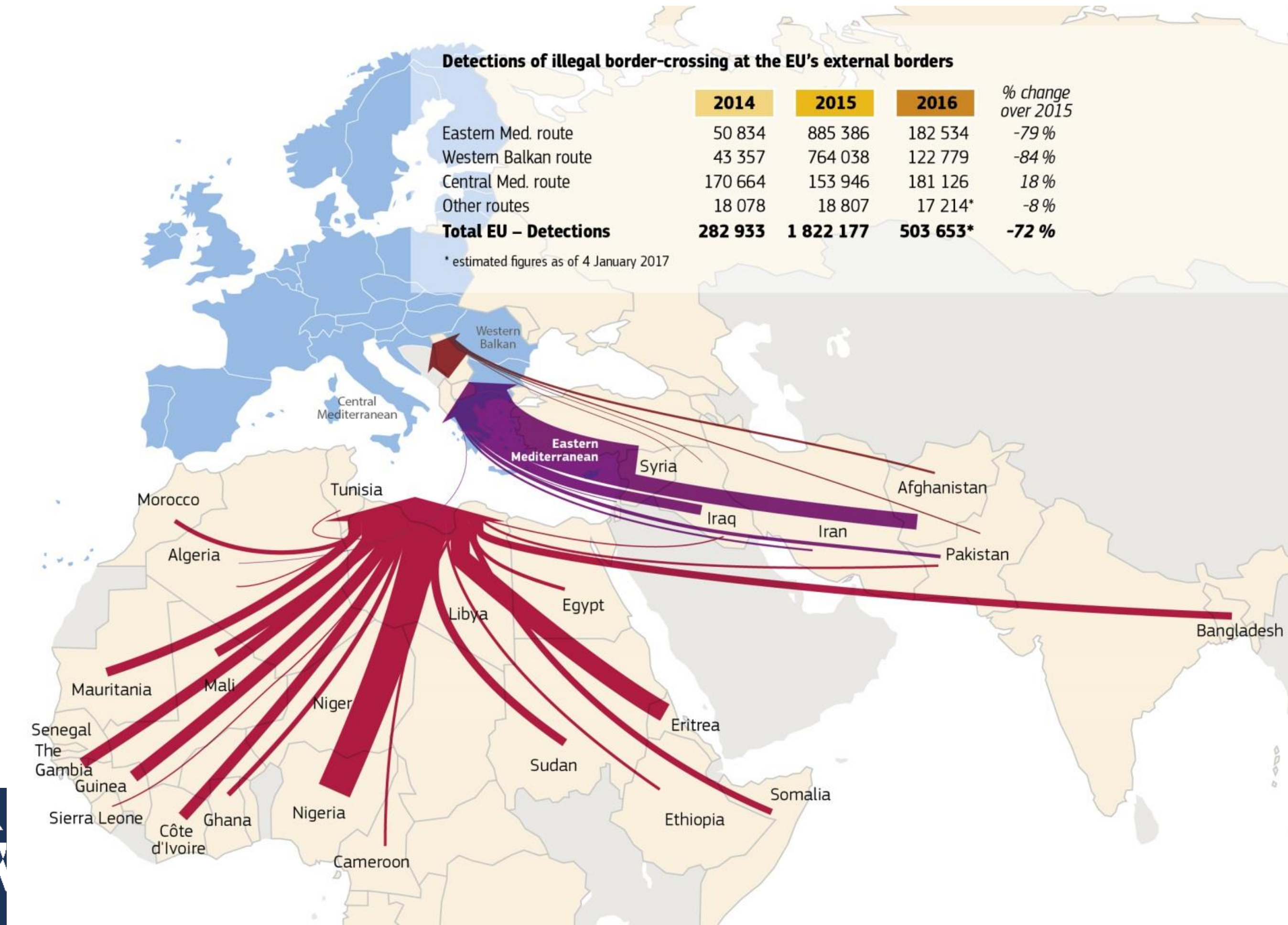
Terrorist Attacks 2012

UNCCD, 2014: *Desertification: The Invisible Frontline*

These three maps of Africa vividly show the concentrations of past terrorist attacks, food riots and other conflicts in areas that are vulnerable to desertification.

Climate-induced migrations

The final result:



Detections of illegal border-crossing at the EU's external borders

	2014	2015	2016	% change over 2015
Eastern Med. route	50 834	885 386	182 534	-79 %
Western Balkan route	43 357	764 038	122 779	-84 %
Central Med. route	170 664	153 946	181 126	18 %
Other routes	18 078	18 807	17 214*	-8 %
Total EU – Detections	**282 933**	**1 822 177**	**503 653***	**-72 %**

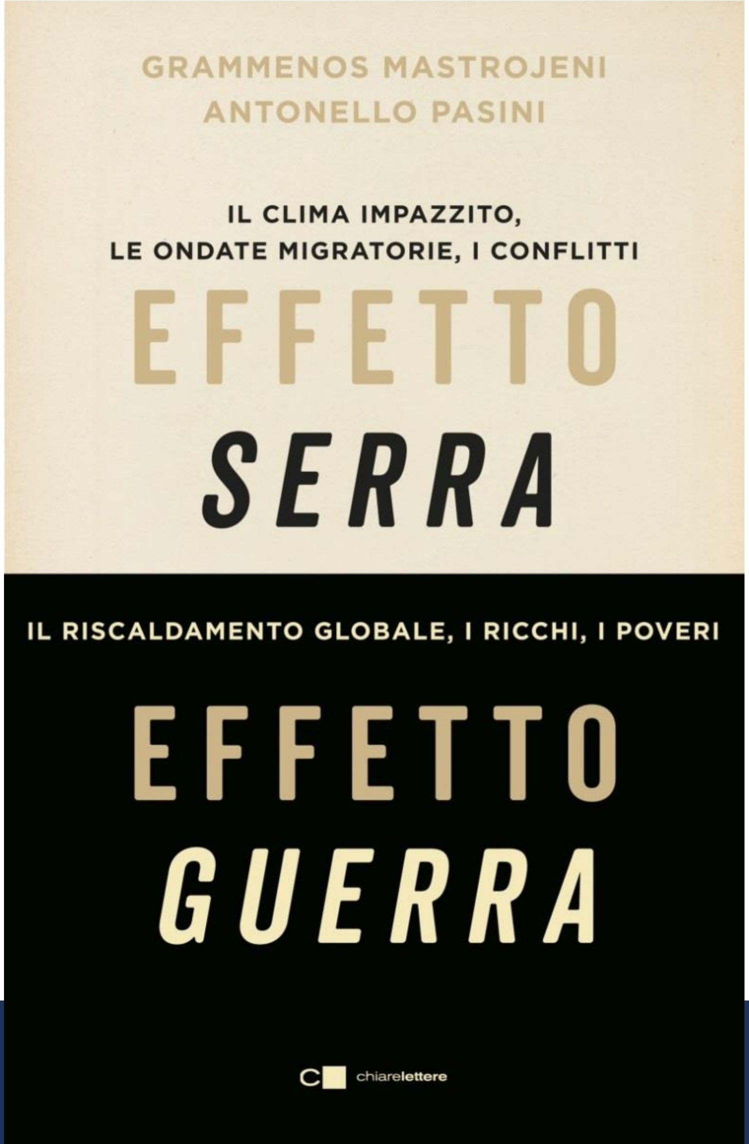
* estimated figures as of 4 January 2017

Climate-induced migrations

Obviously, many causes can be recognized as drivers for the observed migration flows.

However, recently many evidences for a peculiar role of climatic changes in triggering or amplifying conflicts and/or migrations appeared in the scientific literature.

See, for instance…



A study

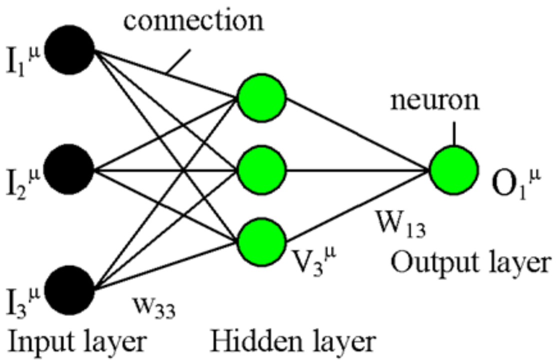
Recent crises may have obscured the role of climate change as a driver of migrations (however, a specific causal role of drought has been recognized also in the devastating Syrian crisis).

Thus, here we limit our analysis to migrations from the Sahelian belt to Italy in the 15 years before the Syrian crisis and the so-called Arabian Spring.

In doing so, even if local crises were of course present in the Sahelian countries also during these years (for instance, the Darfur conflict) and can be causes of migrations, we are confident that we mainly avoid big changes in causes which could overwhelm the direct role of climate change.

A study

Predictors
(climatic data)

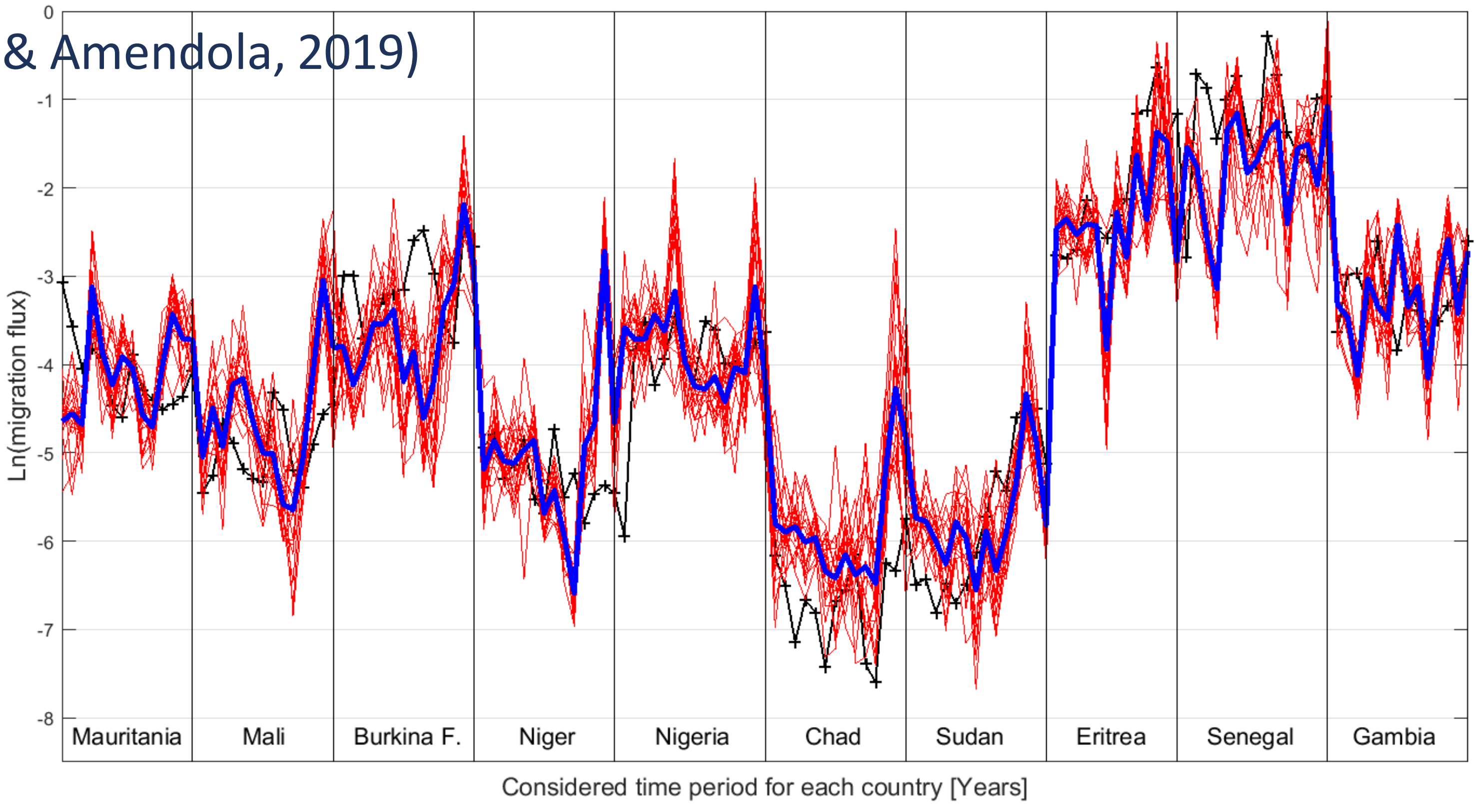


Predictand
(migration flows)

Results

Reconstruction of migrations flows (data: yields, temperature, precipitation, # hours with T>30°C)

(Pasini & Amendola, 2019)



Results (pruning)

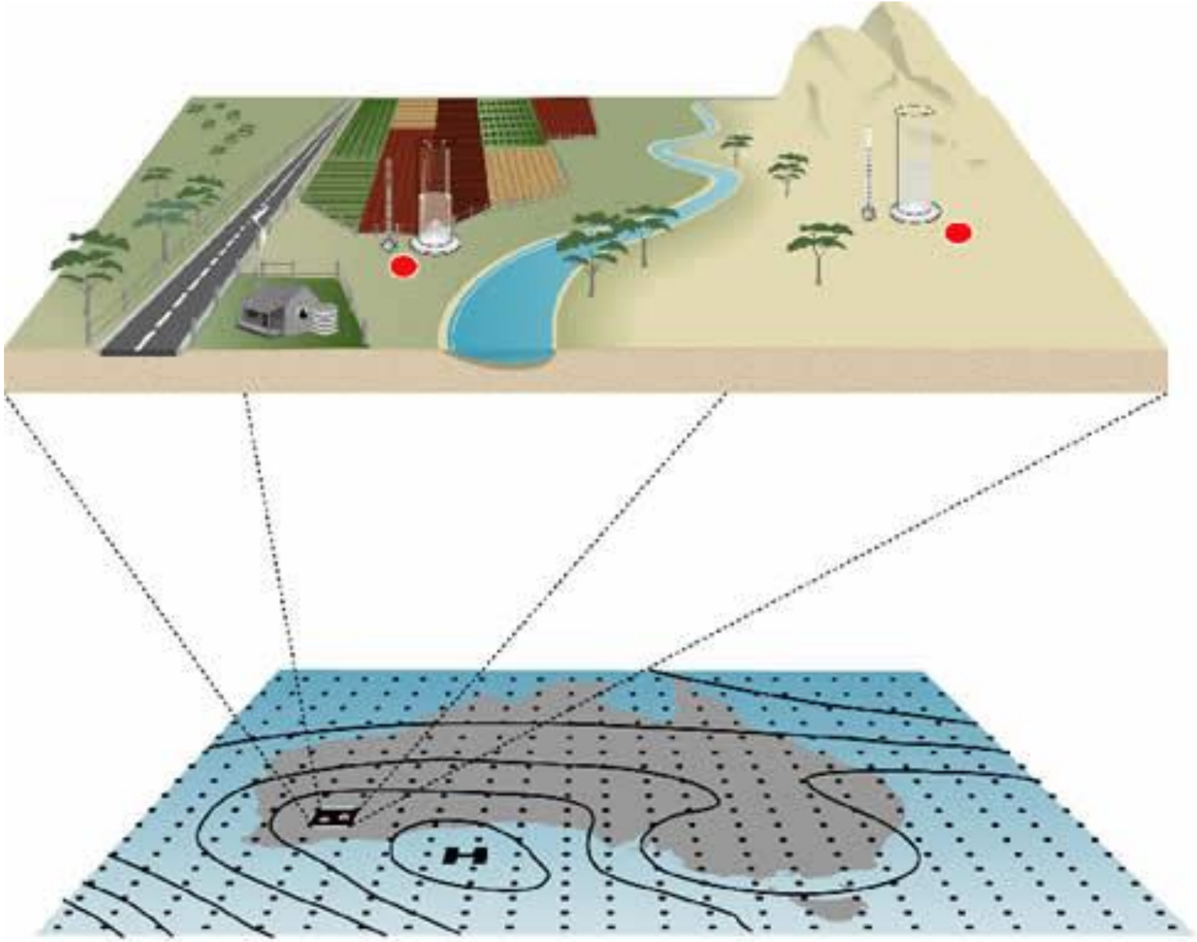
Inputs → Target	NN (R^2)	Multilinear (R^2)
Prec - Temp - # hours T>30°C - Yield →MigFlow	0.775	0.626
Prec - Temp - # hours T>30°C → MigFlow	0.671	0.611
Prec - Temp - Yield → MigFlow	0.683	0.632
Prec - # hours T>30°C - Yield → MigFlow	0.361	0.085
Temp - # hours T>30°C - Yield → MigFlow	0.715	0.447

Yields and # hours with T>30°C have a clear (nonlinear) role in inducing migrations; nevertheless, temperature appears to be more influent. Achieving threshold of physiological tolerance?

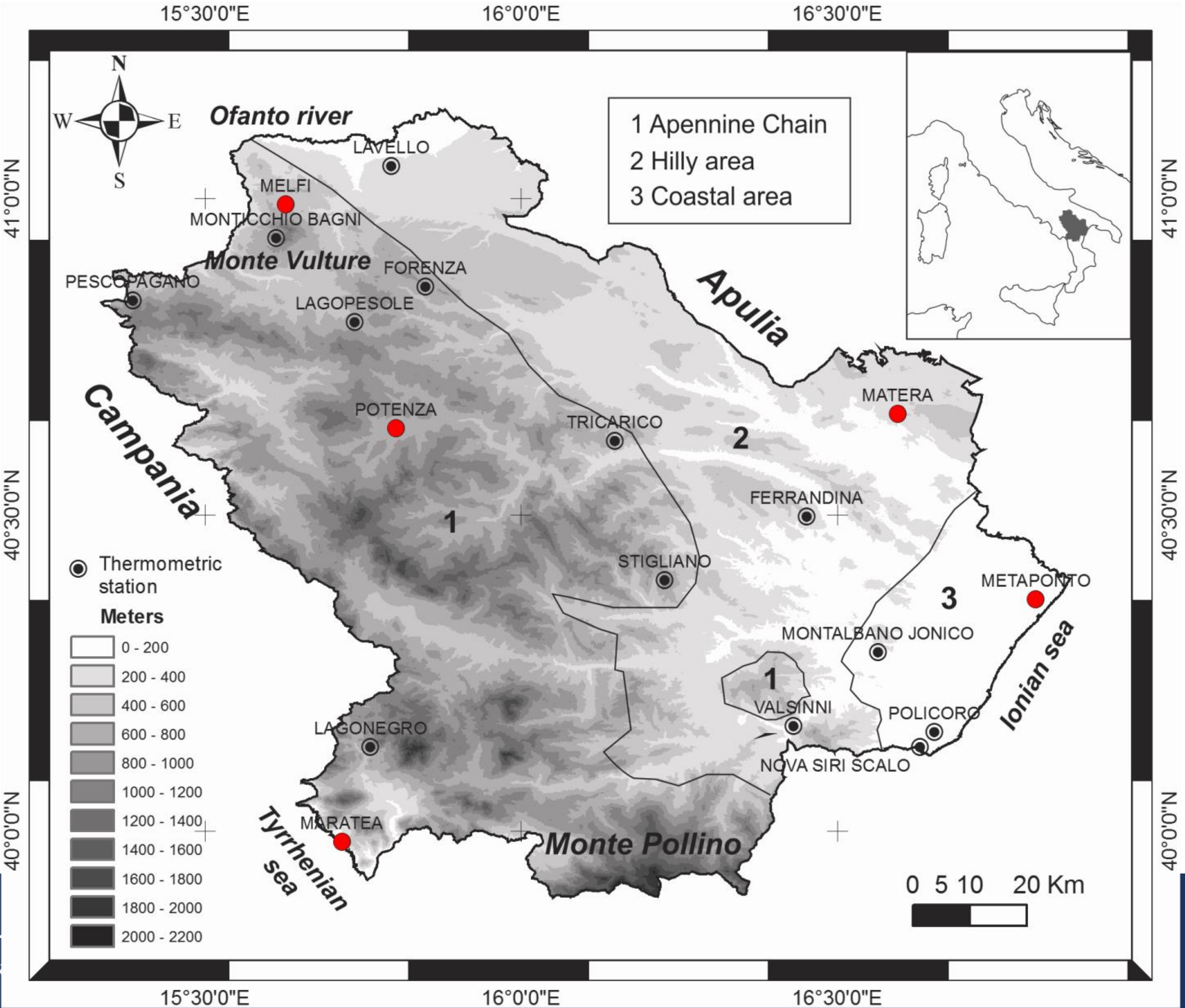
NN downscaling

- Up to now we have considered NNs as a strategy which is alternative to dynamical modeling, but, probably, these strategies can be seen more appropriately as complementary than as alternative.
- A concrete example of “synergies” between them is represented by the case of GCMs downscaling *via* NNs.
- In what follows we will briefly discuss this complementary approach.

The rationale



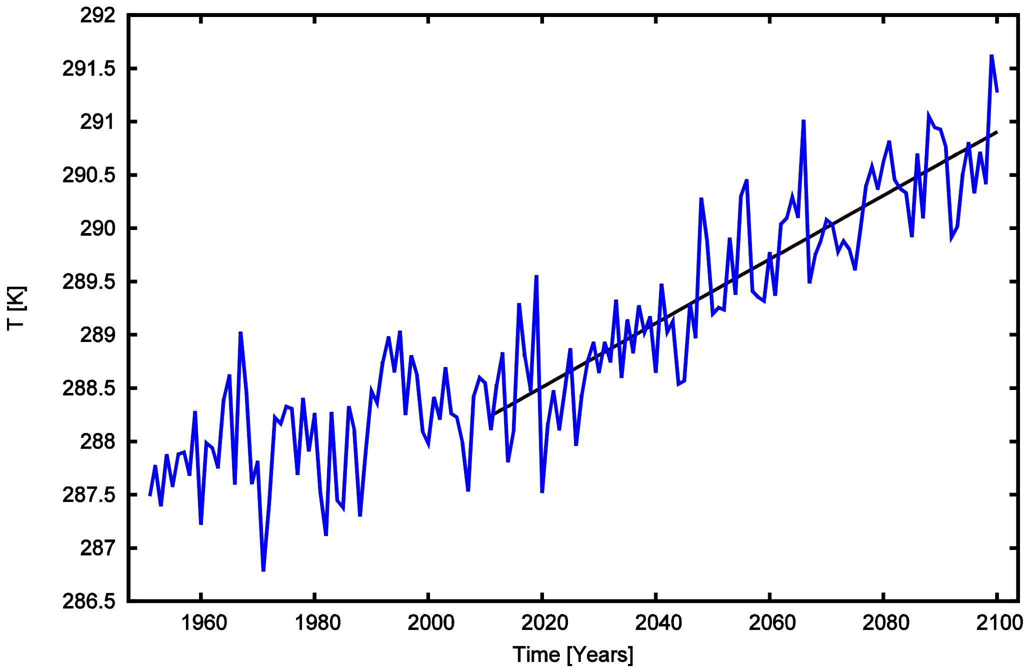
Local projections



Local projections

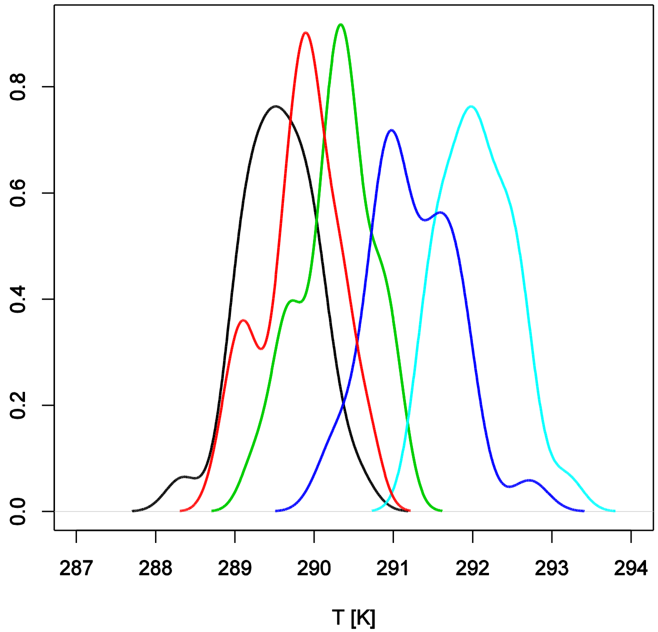
- Bias of the RegCM3 regional model.
- NNs not only correct the bias, but also give better results than a linear model.
- Once we have found the transfer functions in the past location by location, we can apply them to the future outputs of the regional model and obtain local scenarios.
- This is not only for average temperature or precipitation, but also for extreme events over a given scenario.

Local projections



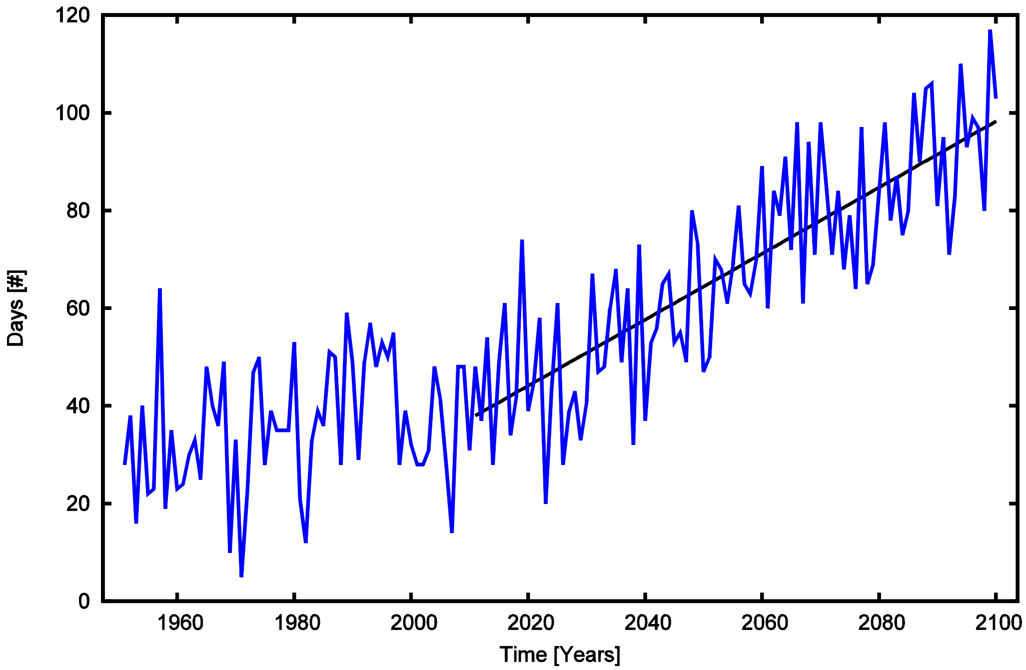
Results of the NN model for annual mean temperatures at Matera site: reconstructed till 2010 and predicted from 2011 to 2100. The black line shows the trend on the predicted values.

Local projections



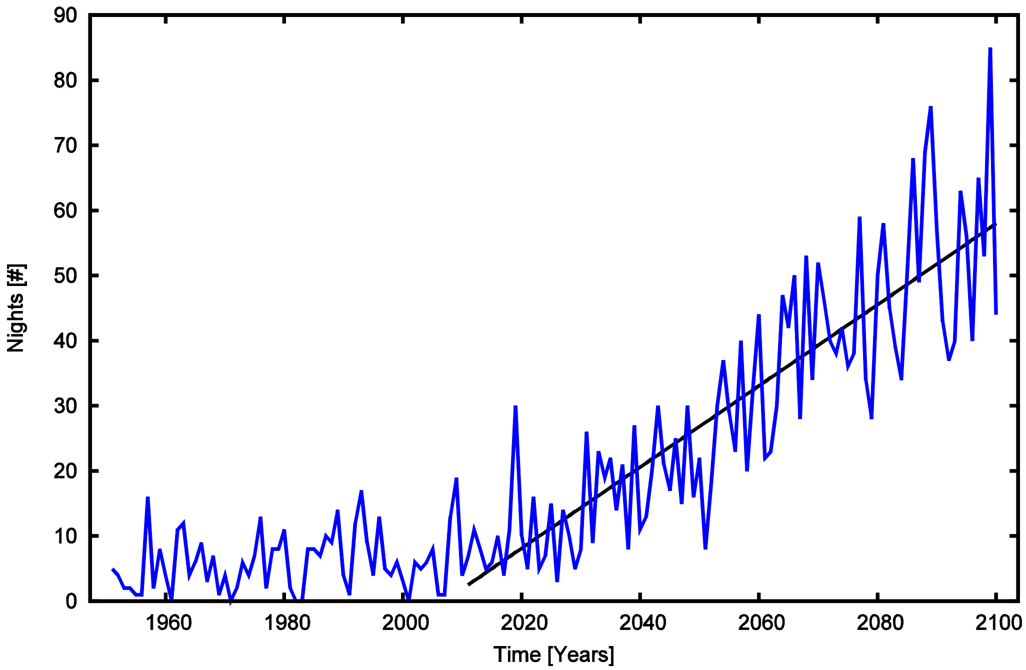
Results of the NN model for density functions of annual mean temperatures over 30-year time intervals at Metaponto site. Black line: 1951-1980, red line: 1981-2010, green line: 2011-2040, blue line: 2041-2070, light blue line: 2071-2100.

Local projections



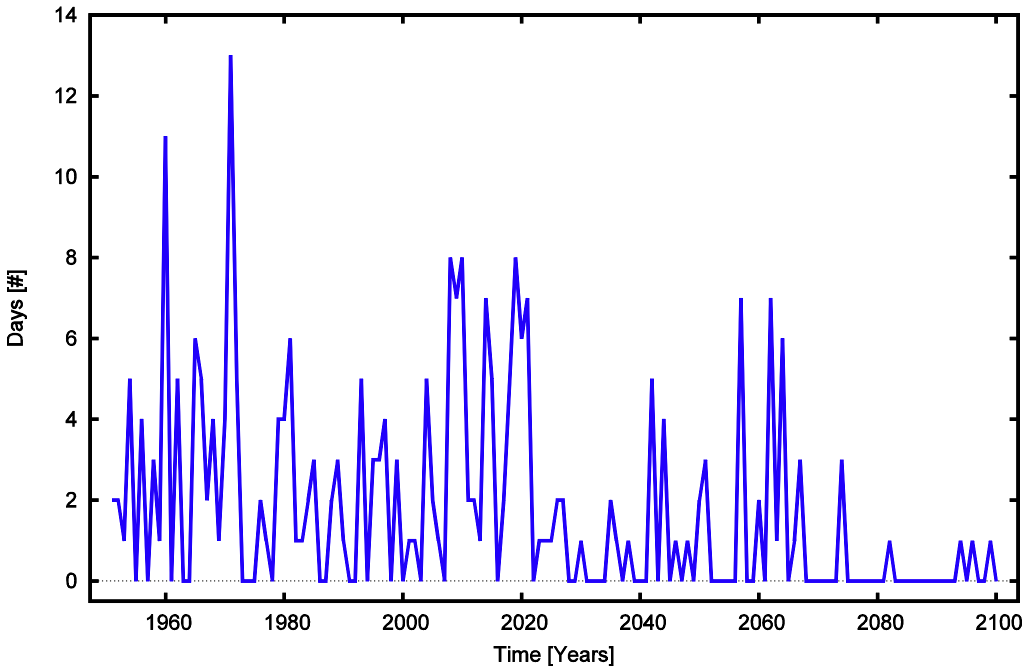
Results of the NN model for the number of hot days in Maratea: reconstructed till 2010 and predicted from 2011 to 2100. The black line shows the trend on the predicted values.

Local projections



Results of the NN model for the number of tropical nights in Melfi: reconstructed till 2010 and predicted from 2011 to 2100. The black line shows the trend on the predicted values.

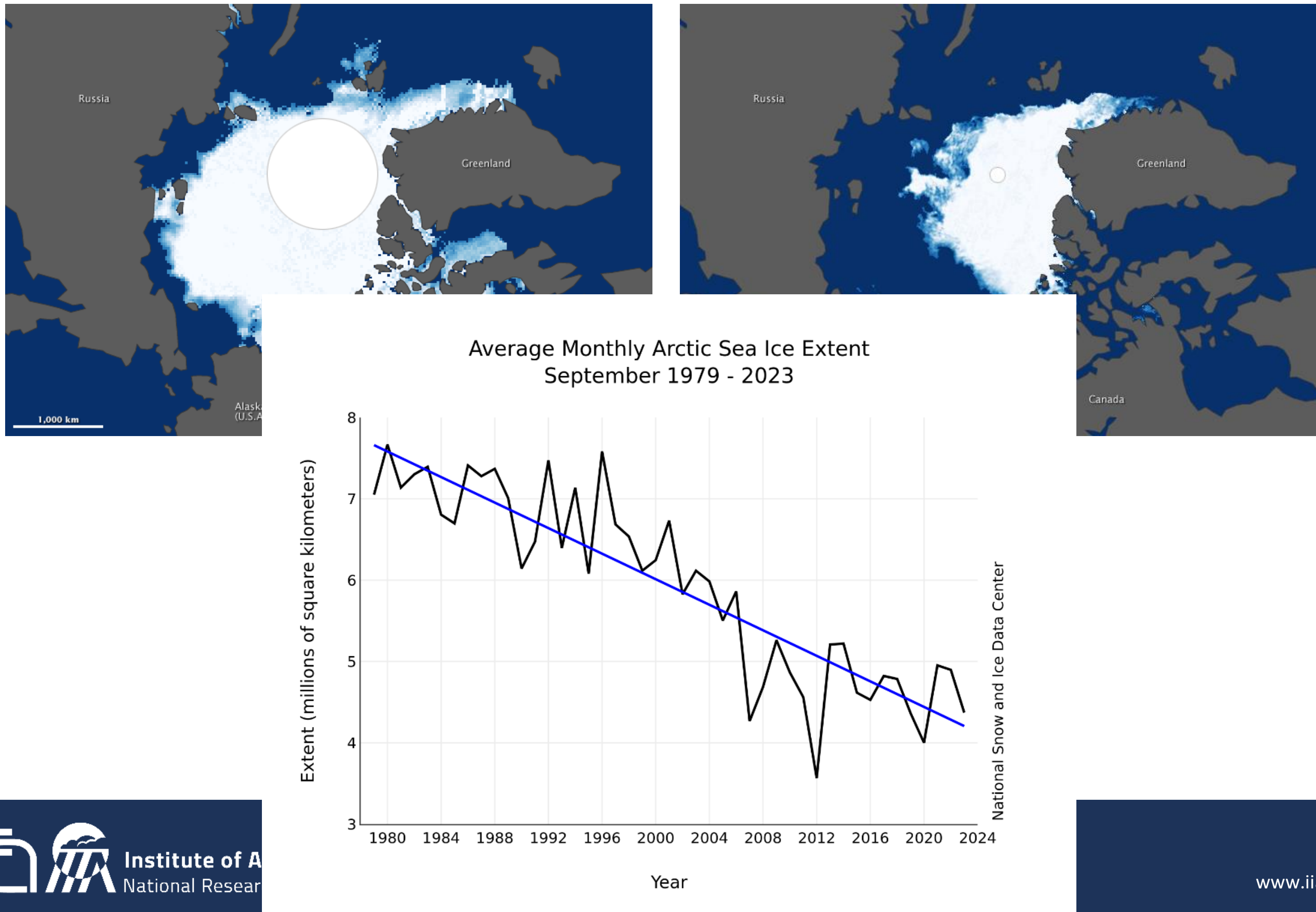
Local projections



Results of the NN model for the number of frost days in Potenza: reconstructed till 2010 and predicted from 2011 to 2100.

The most known observed changes in the Arctic

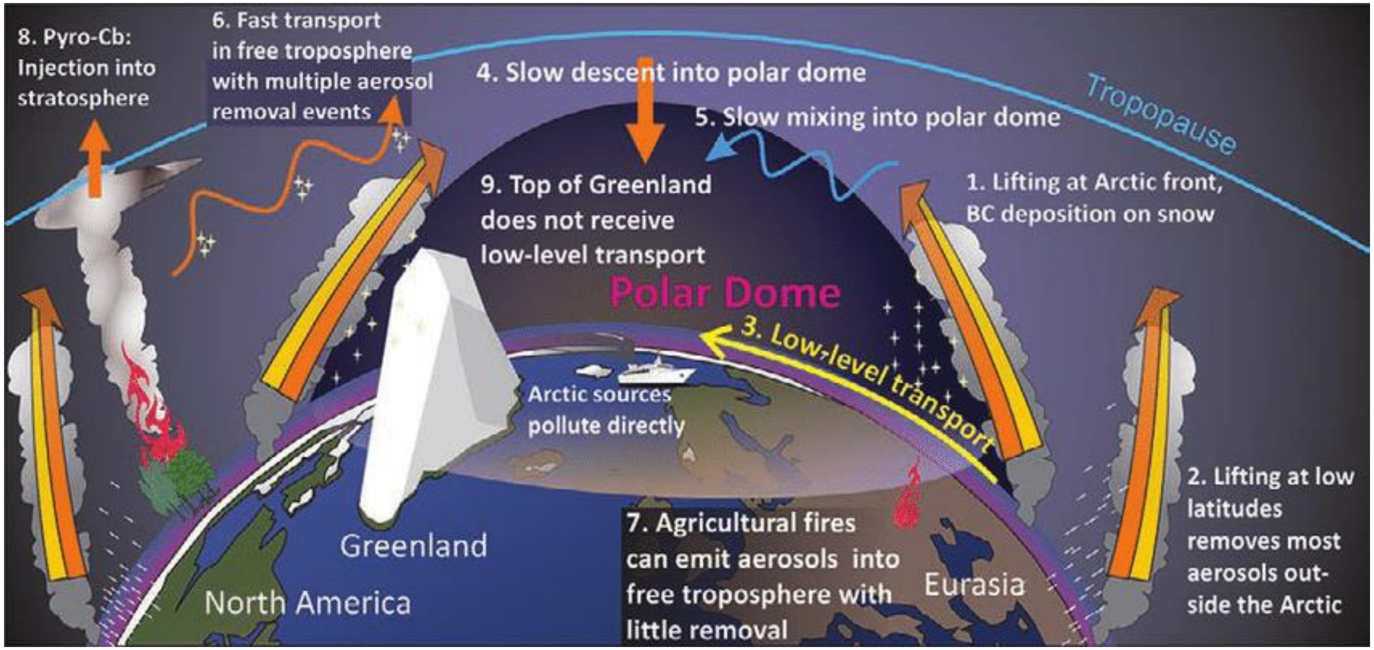
1984



2012

However…

… there are other changes which are less visible, but important



PM10 and our study

- Particulate Matter is cause of concern mainly due to the consequences of its black carbon fraction on the darkening of the ice - and thus its increased melting - along with the impact on local populations' health.
- Although local sources of PM10 in the Arctic are limited nowadays, they are likely to increase in the near future, especially due to intensified ship traffic, which is favored by Arctic ice melting.
- Furthermore, a great deal of the pollution in these regions is due to transboundary transport, which can be particularly strong in cases of significantly high emissions sources, such as wildfires.
- In this framework, the possibility of having reliable short-term forecasts of PM10 concentrations becomes crucial for actions to inform local populations on intense pollution events. This is our goal in the framework of the EU project Arctic PASSION.

At present…

- … forecasts of PM10 in the Arctic region are produced by means of dynamical (meteo-chemical) models with outputs that are available via the Copernicus Services (CAMS).
- Despite the quite high resolution of CAMS models, local forecasts of PM10 concentration show lower performance than in the middle latitudes.
- These difficulties may be due to various factors: inaccurate assimilation aside a poor resolution or the presence of hidden elements of nonlinearity that cannot be grasped from such models are hindrances for a reliable local prediction.
- Thus, a technique such as Neural Networks (NNs) can benefit predictive models of PM10 concentration, as they allow efficient downscaling or model-output post-processing as well as overcoming the issue of hidden nonlinearities.

What we are doing

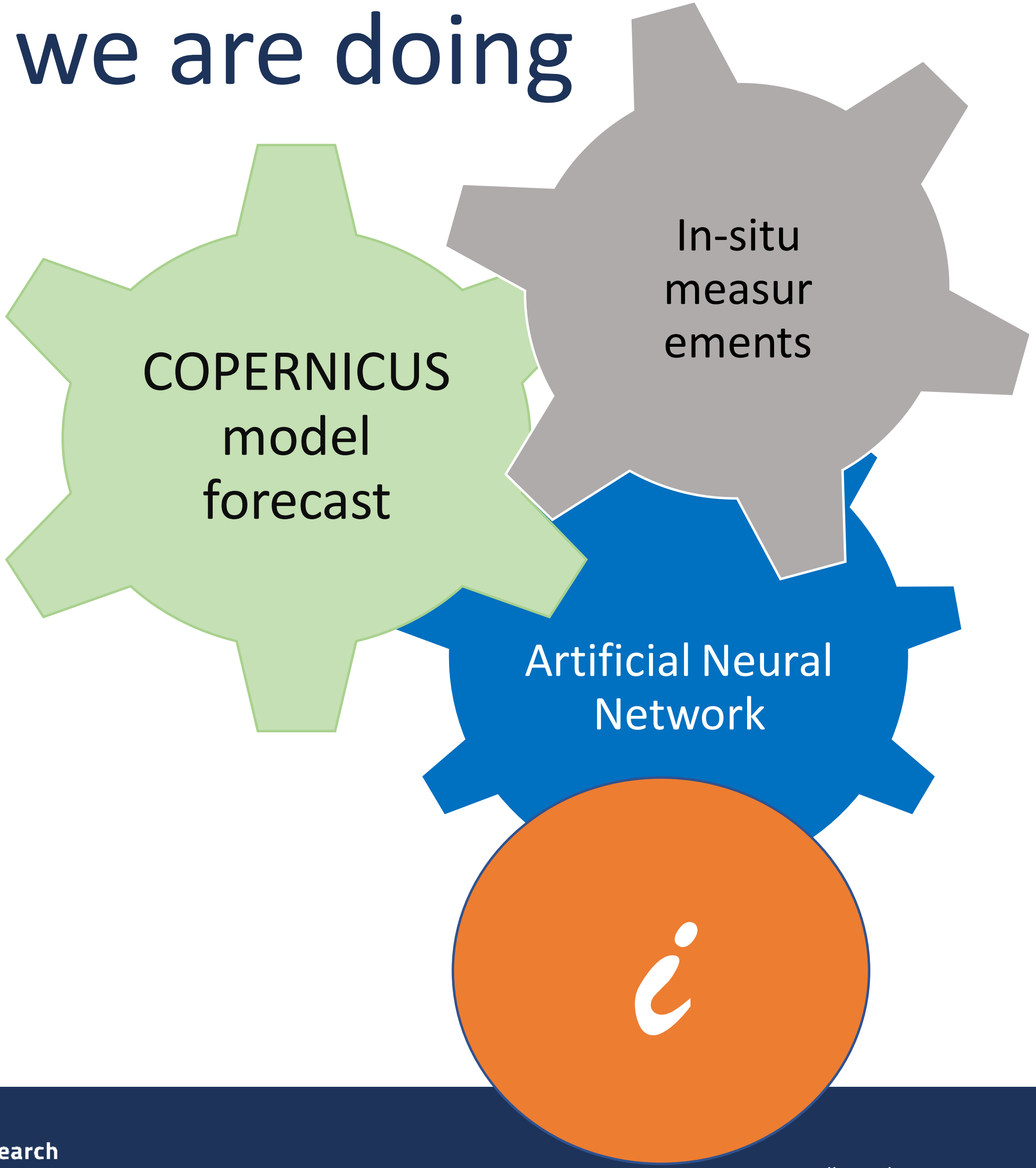
- As a matter of fact, Machine Learning methods have already been applied to these types of problems.
- In the framework of the European project Arctic PASSION, our group adopted a NN modelling strategy in a study involving univariate time series approach to post-process PM10 data produced by an ensemble of ground measurements and nine CAMS models, in order to achieve a 24h forecasts (Fazzini et al., 2023).
- Here, I describe our approach and results, also discussing perspectives of future developments.

What we are doing

We use **local air pollution measurements and meteorological variables** to provide information on **errors of air pollution forecasts** by global and regional models from Copernicus (CAMS).

This information will **improve the accuracy** of **local air pollution forecasts** in real time (by NN application).

It will provide the **feedback to Copernicus** on forecast errors.



Input data

- PM10 time-series (Jun2020 - Jun2023) from 100 selected monitoring stations in Northern Europe (Norway, Sweden, Finland, Iceland)

- Area covered by Copernicus models (10 regional forecast models)

- Daily PM10 CAMS forecasts from 9 models at single grid points

- Daily weather analysis and forecast for meteorological variables (wind speed, temperature and planetary boundary layer)

Input data

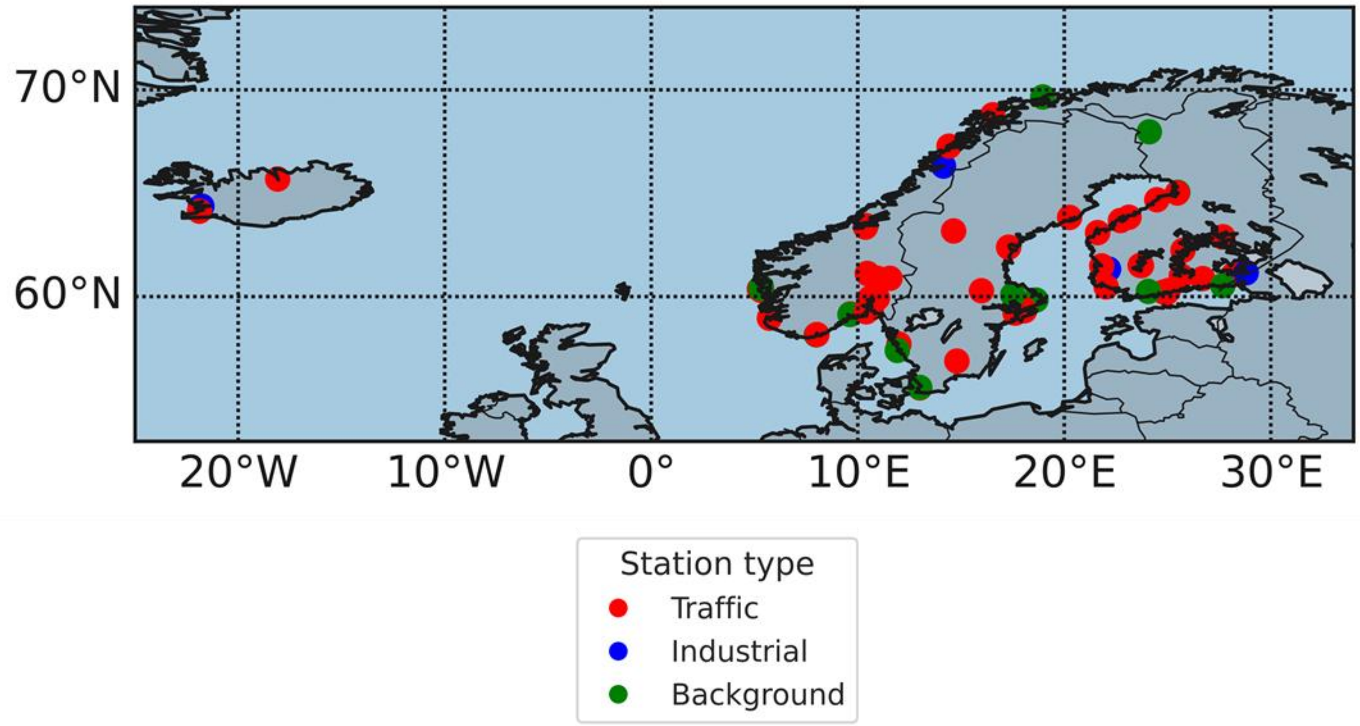


Fig.1: Monitoring stations selected for the upcoming study. The stations types depends on the EEA classification of PM_{10} main sources.

Input data

Table 1. Air quality monitoring stations selected for this forecasting study with their geographical positions and PM_{10} measurements techniques.

Station	Country	Latitude	Longitude	Measure	Source	Code
Muonio Sammaltunturi	Finland	67.97	24.12	TEOM [1]	FMI	101983
Kópavogur Dalsmári	Iceland	64.10	−21.89	BAN [2]	EEA	52109
Grundartangi Gröf	Iceland	64.33	−21.83	BAN [2]	EEA	52149
Pyykösjärvi (Oulu)	Finland	65.04	25.50	TEOM [3]	EEA	15557
Tromso Rambergan	Norway	69.65	18.96	TEOM [1]	EEA	62993
Oulun keskusta 2 (Oulu)	Finland	65.01	25.47	TEOM [1]	EEA	15609

[1] Tapered Element Oscillating Microbalance. [2] Beta Attenuation and Nephelometry. [3] Beta Attenuation by a two-beam compensation method.

Input data

Table 2. Main characteristics of the air quality regional models used by CAMS [34,35].

Model	Institution	Horizontal Resolution	Vertical Resolution	Assimilated Measurements
CHIMERE	INERIS [1]	$0.1^o \times 0.1^o$	8 levels, top at 500 hPa	O_3 and PM_{10} from surface stations
EMEP	MET Norway [2]	$0.25^o \times 0.125^o$	20 levels, top at 100 hPa	NO_2 columns from OMI/Aura remote sensing and NO_2 from surface stations
EURAD-IM	RIU UK [3]	15 km, Lambert conformal projection	23 levels, top at 100 hPa	O_3, NO, NO_2, SO_2, CO, PM_{10}, $PM_{2.5}$ from surface stations, NO_2 from remote sensing column retrievals, CO profiles
LOTOS-EUROS	KNMI [4]	$0.25^o \times 0.125^o$	34 levels, top at 3.5 km	O_3 from surface stations
MATCH	SMHI [5]	$0.2^o \times 0.2^o$	52 levels top at 300 hPa	O_3, NO_2, CO, PM_{10}, $PM_{2.5}$ from surface stations
MOCHAGE	Météo France	$0.2^o \times 0.2^o$	47 levels, top at 5 hPa	O_3 from surface stations
SILAM	FMI [6]	$0.15^o \times 0.15^o$	8 levels, top at 6.7 km	O_3, NO_2 and SO_2 from surface stations
GEMA-Q	IEP-NRI [7]	$0.1^o \times 0.1^o$	28 levels, top at 10 hPa	O_3, NO_2, CO, SO_2, PM_{10}, $PM_{2.5}$ from surface stations
DEHM	AARHUS UNIVERSITY Denmark	18 km, polar streographic projection	29 layers, top at 100 hPa	O_3 and NO_2 from surface stations, PM_{10} and $PM_{2.5}$ from global CAMS forecast

[1] Institut National de l'Environnement Industriel et des Risques. [2] Meteorologisk institutt, Norway. [3] Rheinisches Institut Für Umweltforschung an der Universität zu Köln E. V., Germany. [4] Koninklijk Nederlands Meteorologisch Instituut, the Netherlands. [5] Sveriges Meteorologiska och Hydrologiska Institut, Sweden. [6] Ilmatieteen Laitos, Finland. [7] Institute of Environmental Protection, Poland.

The neural network approach

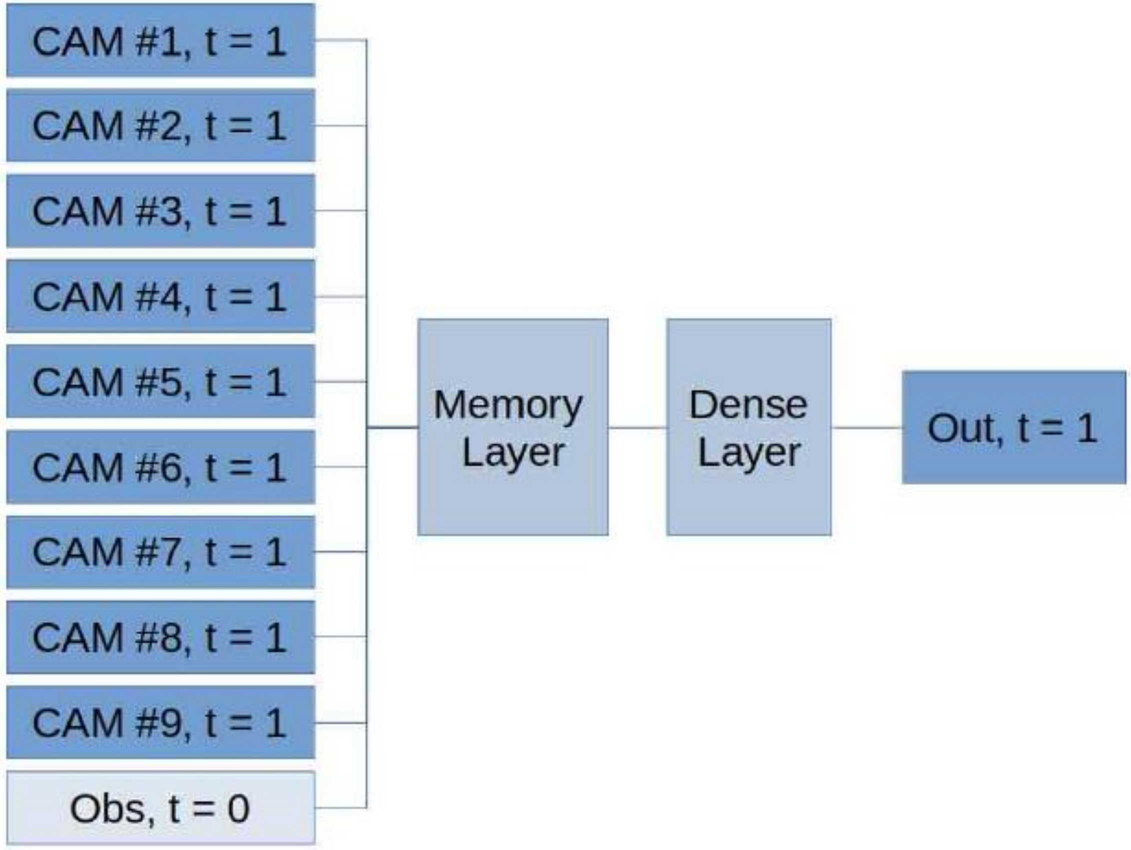


Figure 2. General architecture. 'CAMS #n' indicates the n_{th} CAM model.

The neural network models

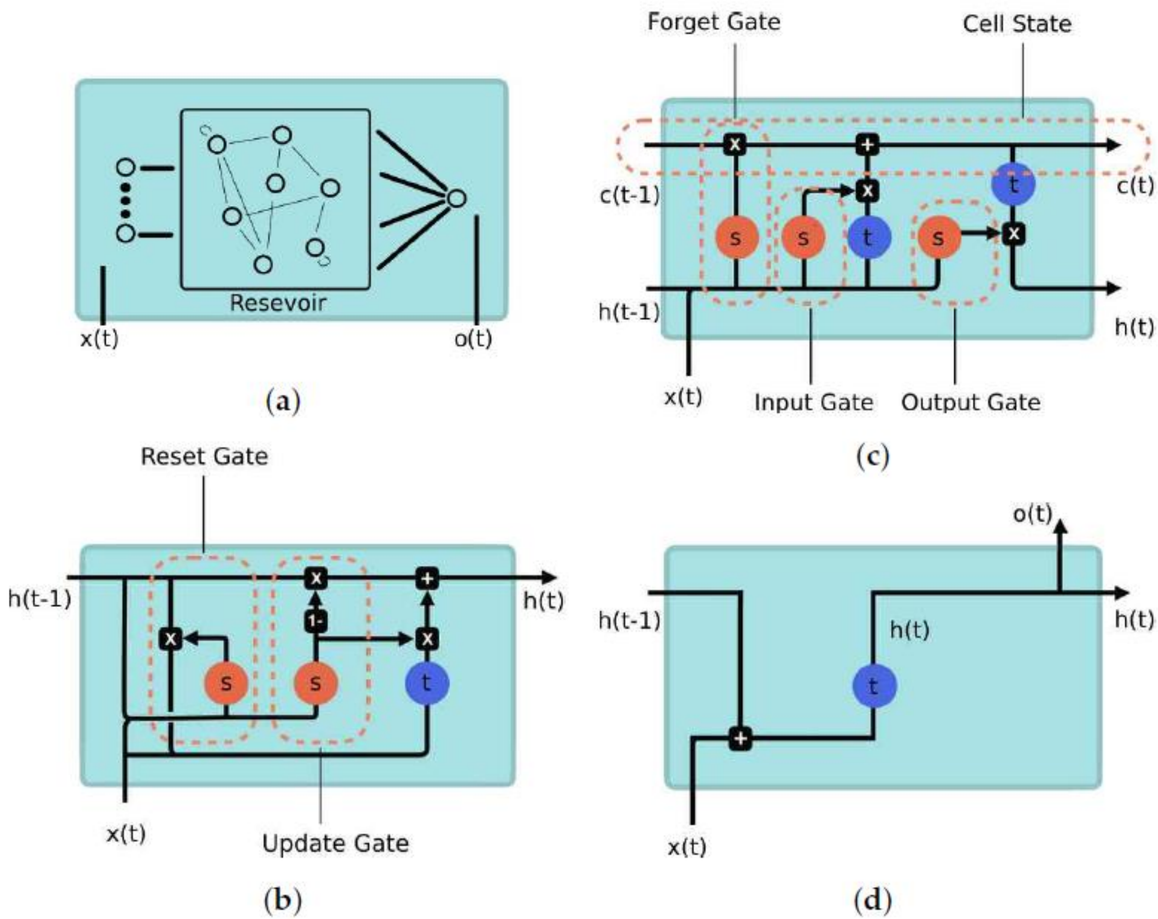


Figure 3. Various alternatives for the memory layer: (**a**) ESN. (**b**) GRU. (**c**) LSTM. (**d**) RNN.

(a) = Echo State Network

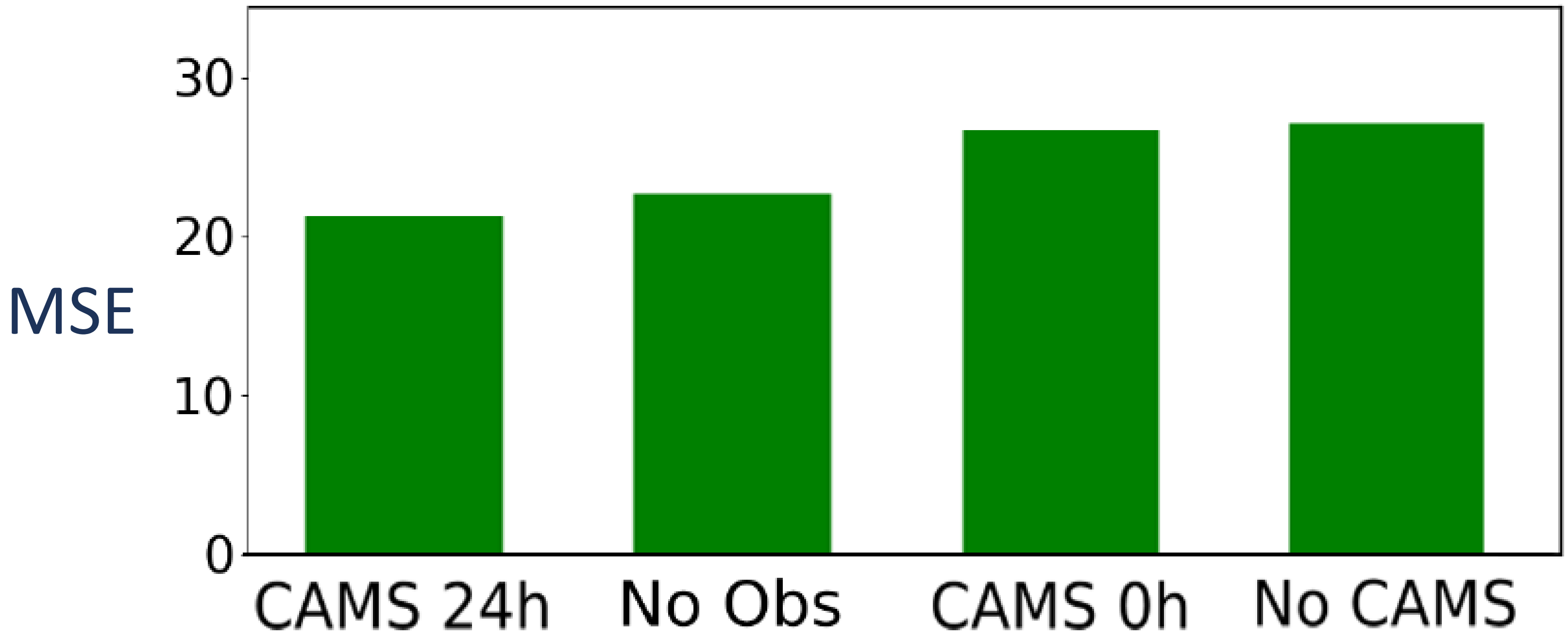
(b) = Gated Recurrent Unit network

(c) = Long Short-Term Memory network

(d) = Recurrent Neural Network

Results

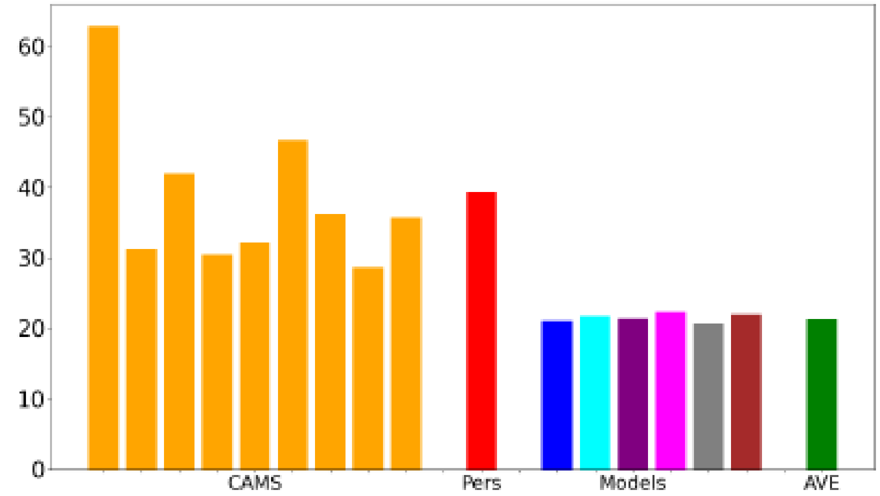
Inputs pruning



Results

Prediction performance

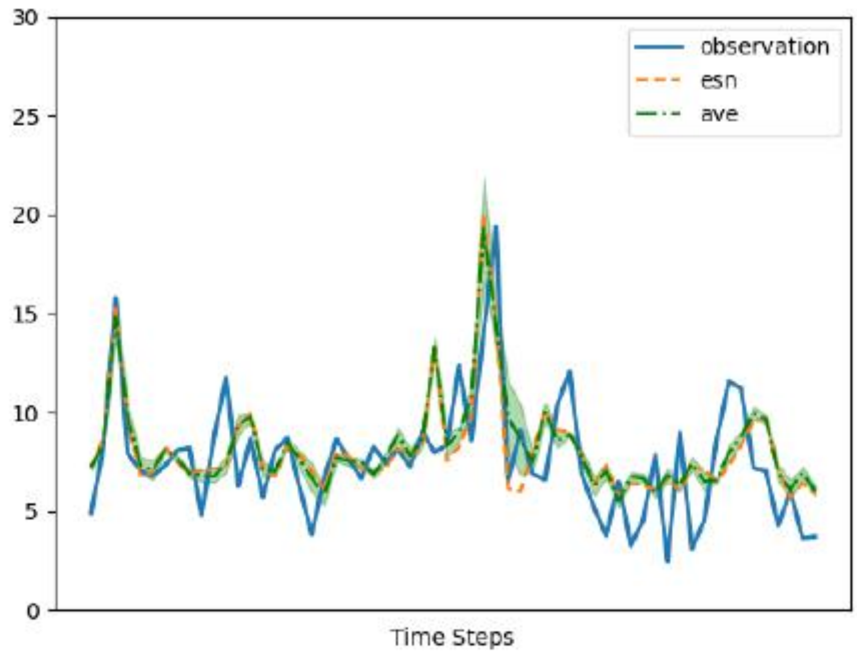
MSE
$(\mu g/m^3)^2$



Results

Prediction performance

PM10
conc.
(µg/m³)



Perspectives

After this univariate analysis, our aim is to perform a multivariate one, by including CAMS model outputs about wind (speed and direction), temperature and height of the boundary layer.

The presence of these endogenous variables will certainly lead to better performance due to the insertion into the NN models of an explicit forecast of the status of the low atmosphere and of the transport into the Arctic of air masses coming from lower latitudes.

Finally, a consistent improvement is expected by an assimilation of PM data from wildfires. We are studying the best way to introduce this in our framework.

Conclusions for Arctic PM10

The application of NN models to the problem of PM forecast in the Arctic have shown that they are able to post-process the outputs of CAMS models and achieve better forecasting results than those obtained by the former models.

This kind of study can be key in the realm of the Arctic PASSION project, when dealing with local communities and local policy makers. In fact, even if usually PM10 concentration is quite low in the aforementioned areas, people are unprepared to peak events, when forecast is instead decisive in order to take efficient adaptative measures.

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