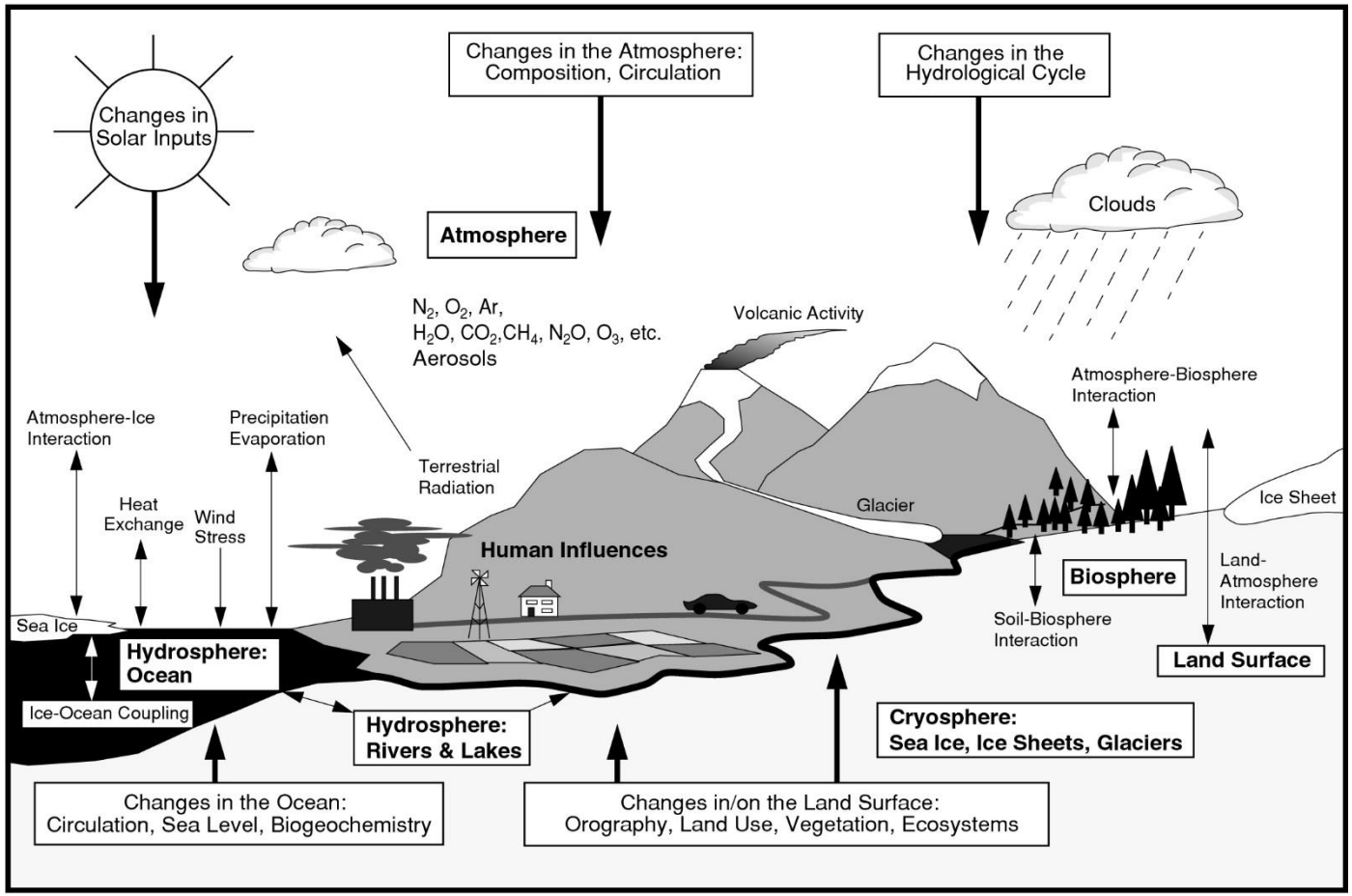
Può l'intelligenza artificiale contribuire allo studio del clima?

Antonello Pasini, Fisico del clima, CNR, Roma

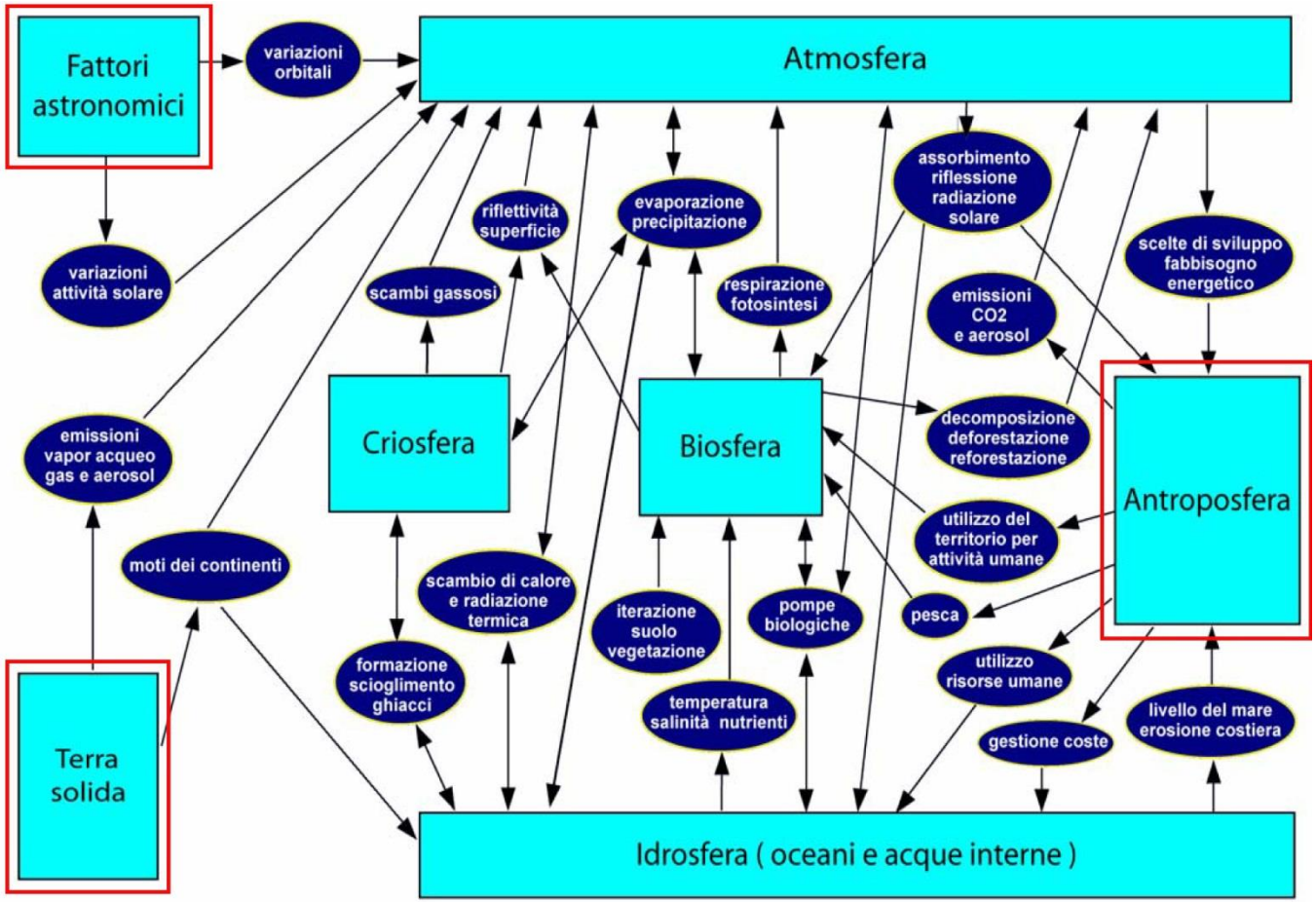
Un’analisi in 4 esempi

- Attribuzione delle cause del riscaldamento globale
- Natura dell’Atlantic Multidecadal Oscillation
- Cause delle migrazioni umane dal Sahel all’Italia
- Scenari climatici a livello locale

Il clima è un sistema complesso



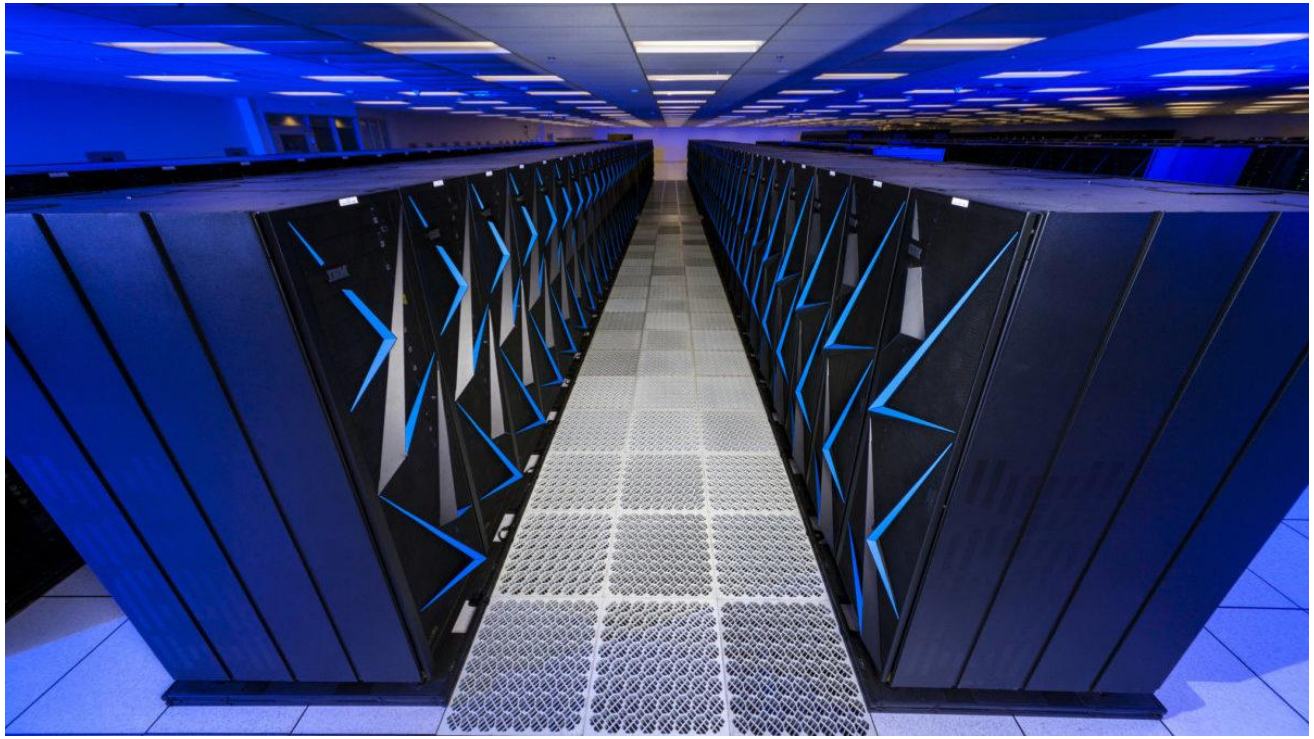
Il clima è un sistema complesso



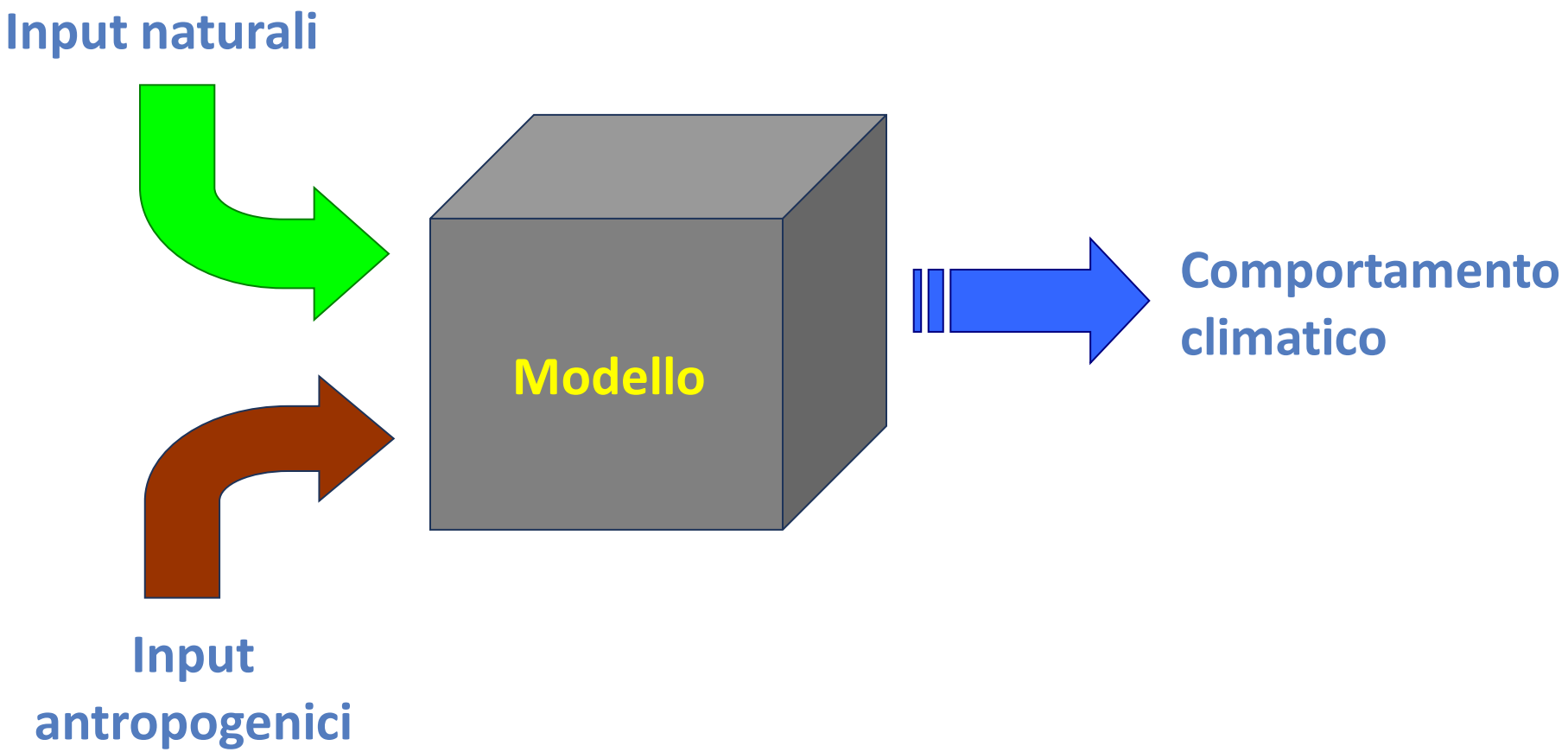
Adattata da Lionello, 2006

Di fronte alla complessità

Da un laboratorio reale ad un laboratorio virtuale:

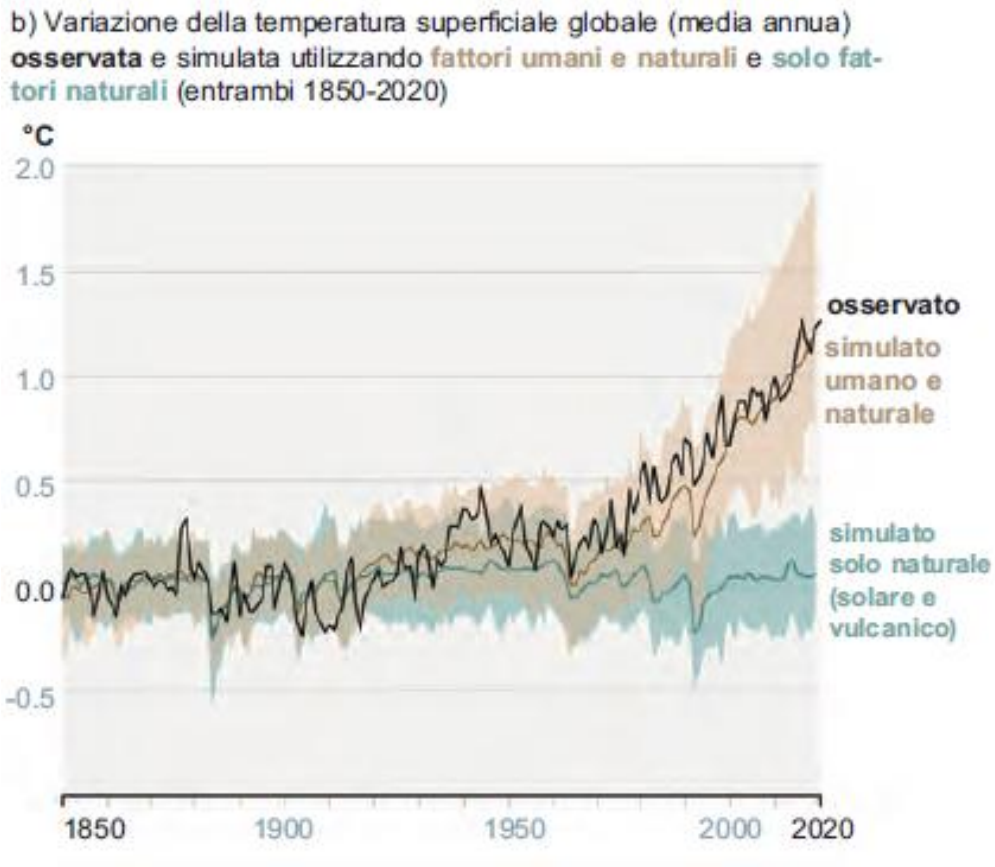


L’analisi delle cause



Attribuzione delle cause

Modelli dinamici: Global Climate Models (GCMs)



Linea beige:

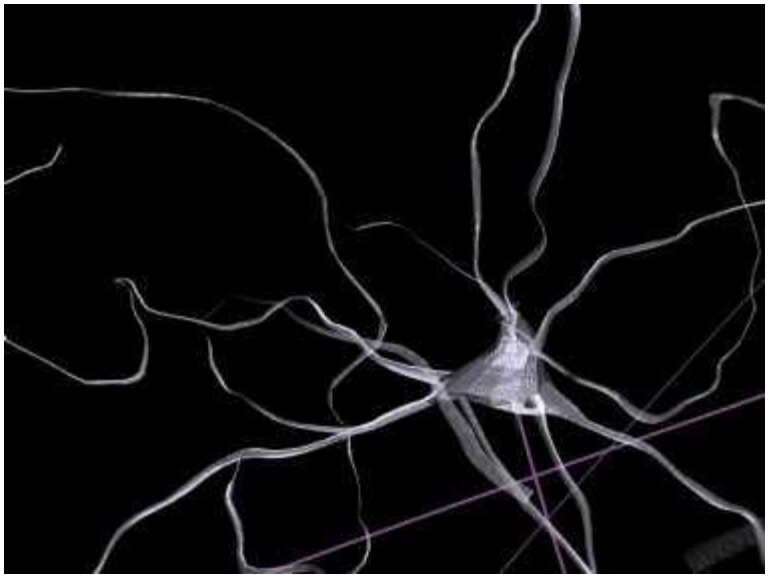
Diamo al modello tutti i valori realmente osservati delle forzanti

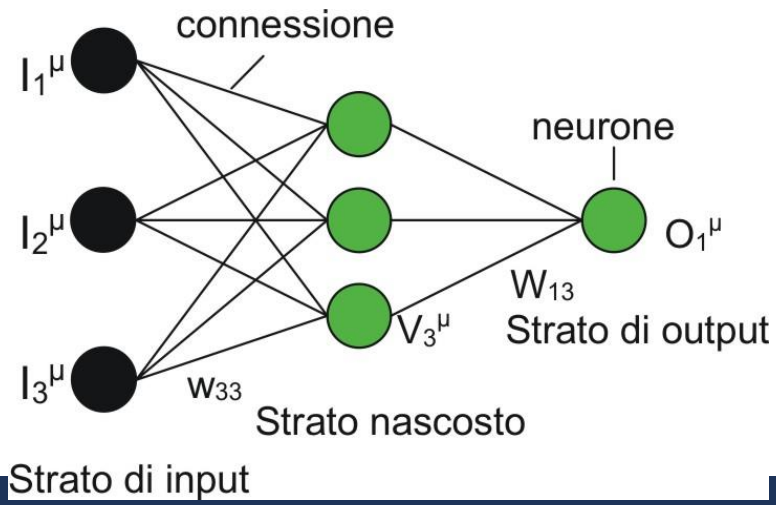
Linea azzurra:

Le forzanti antropogeniche sono tenute fisse ai valori costanti del 1850

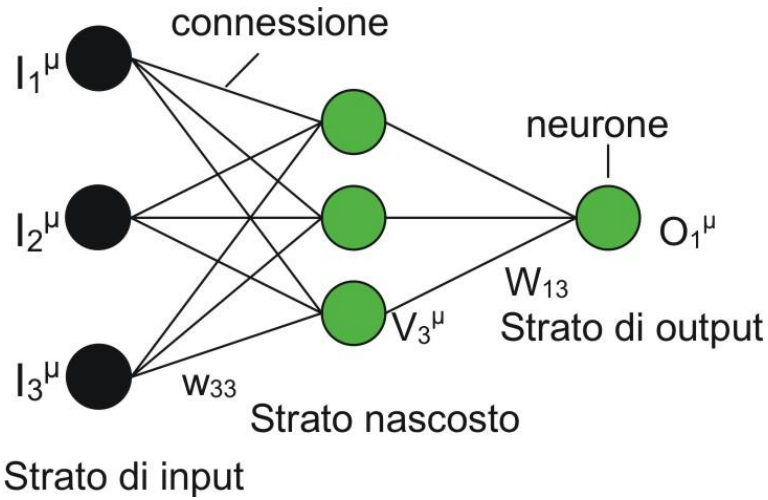
Adattata da IPCC, 2021

Una strategia differente





Il tool di reti neurali



Multi-Layer Perceptrons (MLPs) abbastanza standard:

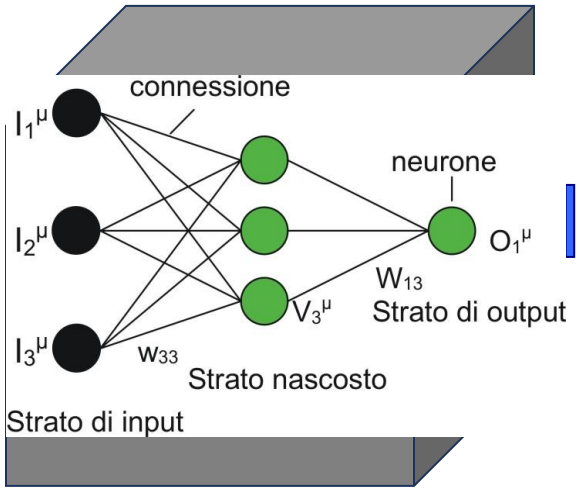
- Reti feed-forward con un hidden layer;
- Metodo di back-propagation classico o quasi-Newtoniano: algoritmo di Broyden-Fletcher-Golfarb-Shanno (BFGS) (nuovo).

Un tool specifico per datasets storici corti:

- ensemble leave-one-out con early stopping (vedi Pasini, 2015).

Un modello a rete neurale

Input naturali



Comportamento climatico

Input antropogenici

Ricostruzioni neurali

www.nature.com/scientificreports

OPEN

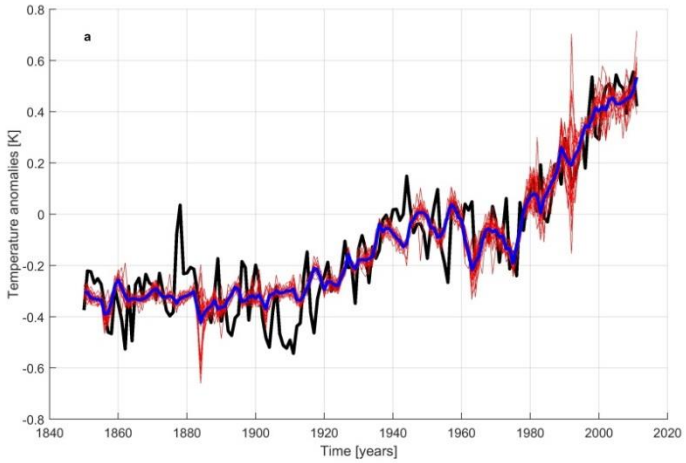
Attribution of recent temperature behaviour reassessed by a neural-network method

Received: 21 August 2017
Accepted: 24 November 2017
Published online: 15 December 2017

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

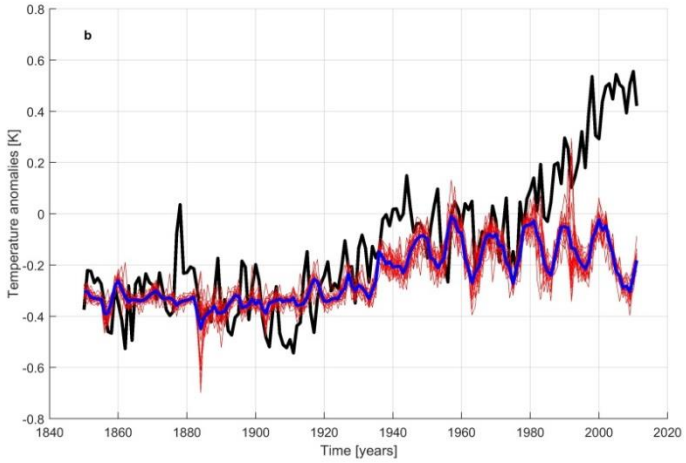
Attribution studies on recent global warming by Global Climate Model (GCM) ensembles converge in showing the fundamental role of anthropogenic forcings as primary drivers of temperature in the last half century. However, despite their differences, all these models pertain to the same dynamical approach 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.

Ricostruzioni neurali



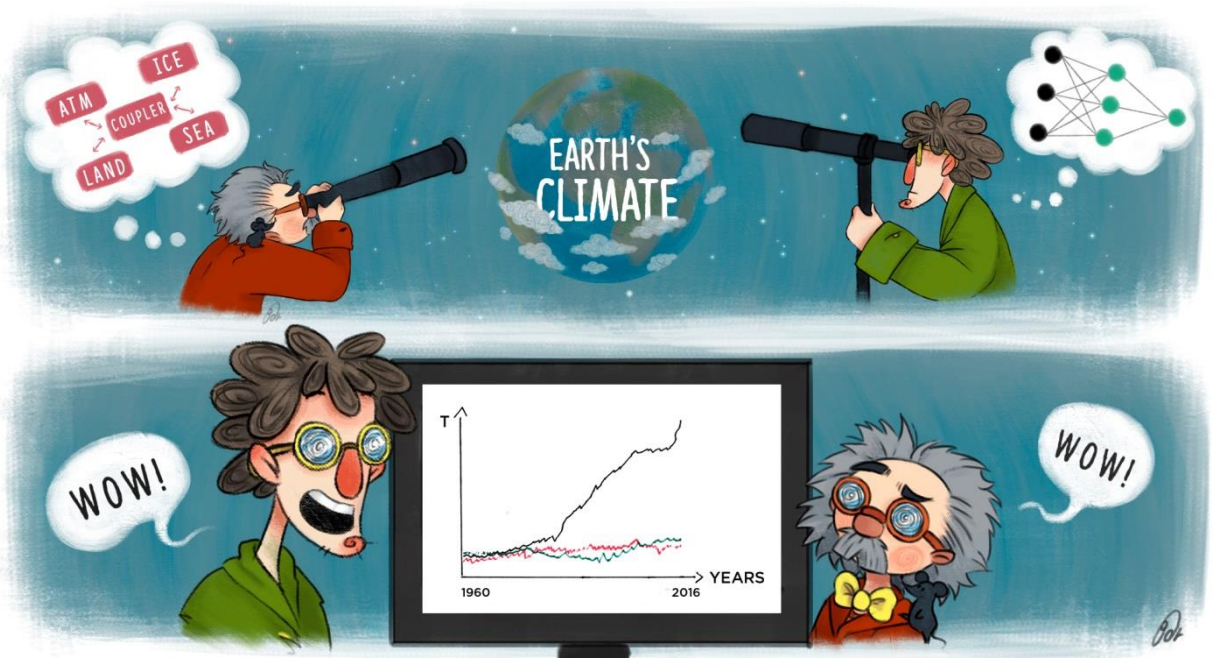
Con forzanti naturali e antropogeniche reali

Pasini et al., 2017



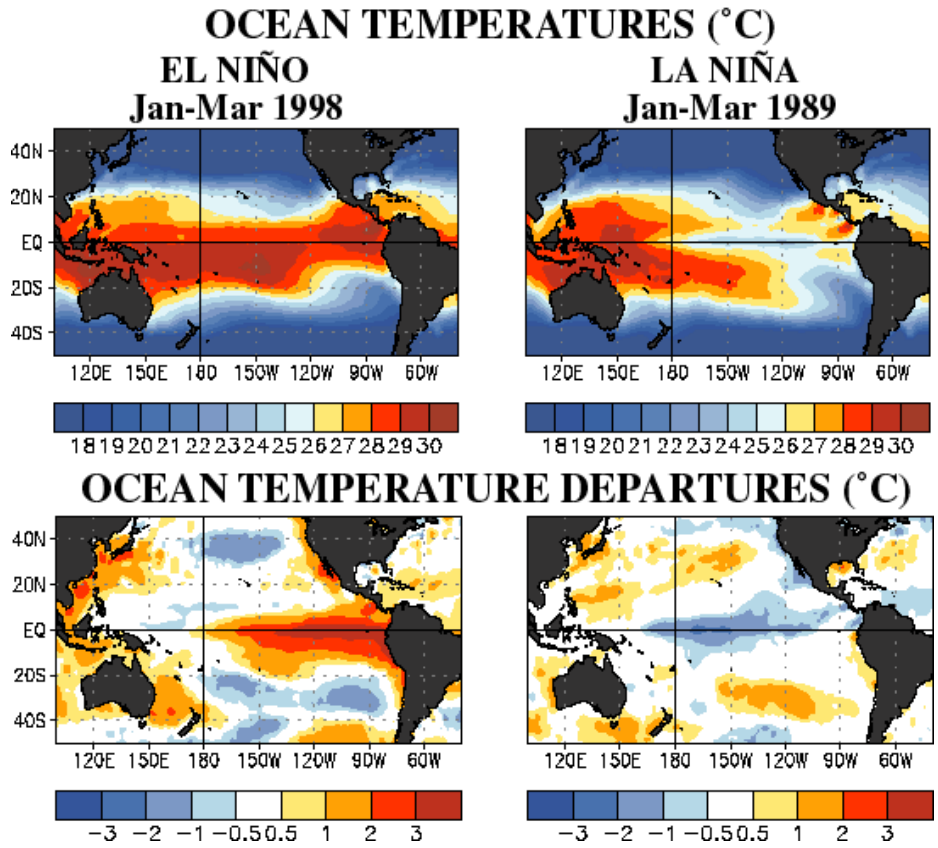
Con forzanti antropogeniche ferme al 1850

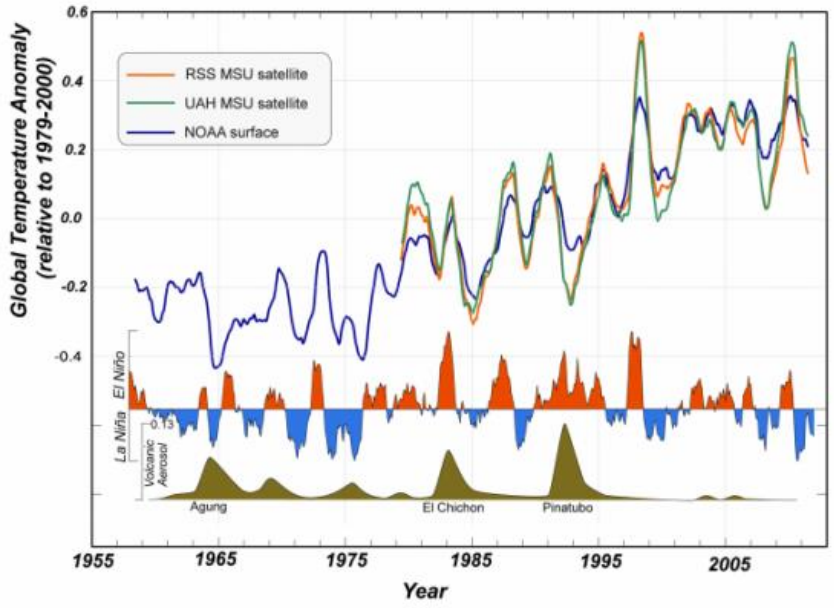
Robustezza


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

Variabilità naturale

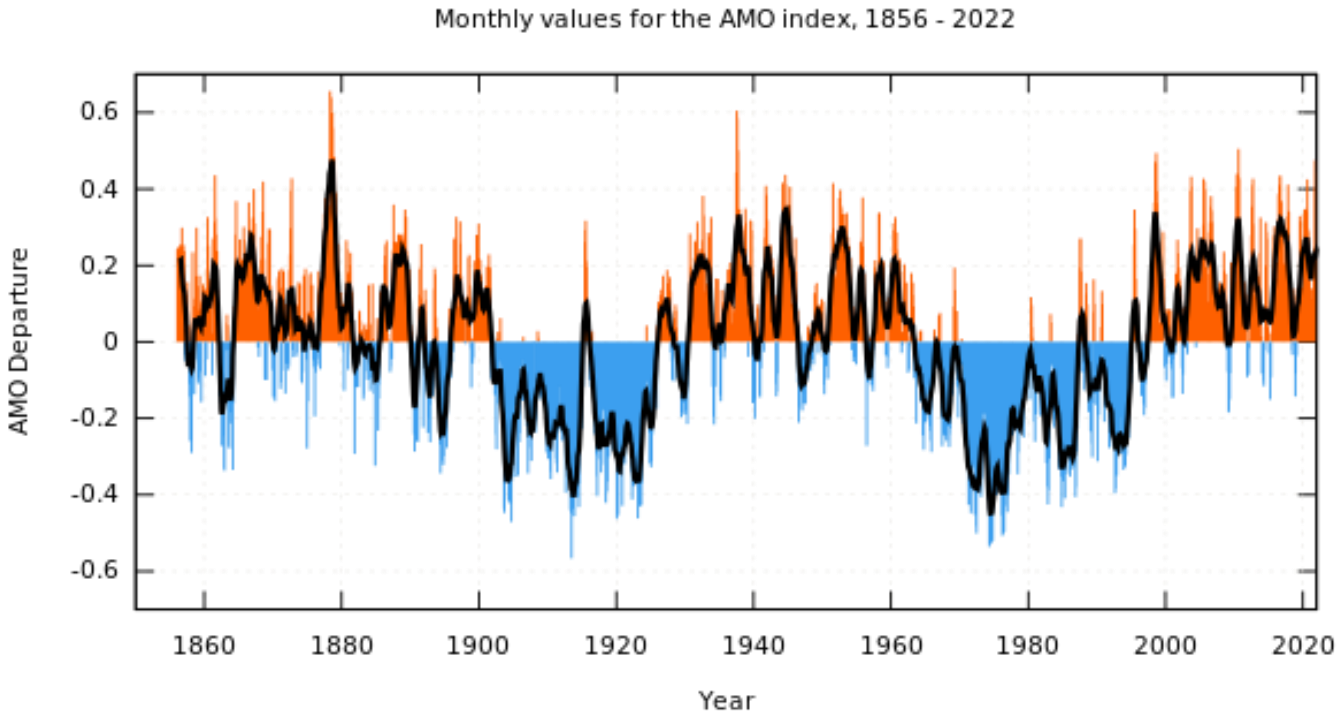
El Niño Southern Oscillation (ENSO)





Variabilità naturale

Atlantic Multidecadal Oscillation (AMO)



Variabilità naturale

Atlantic Multidecadal Oscillation (AMO)

Theoretical and Applied Climatology (2022) 150:881–892
https://doi.org/10.1007/s00704-022-04207-0

RESEARCH

Is natural variability really natural? The case of Atlantic Multidecadal Oscillation investigated by a neural network model

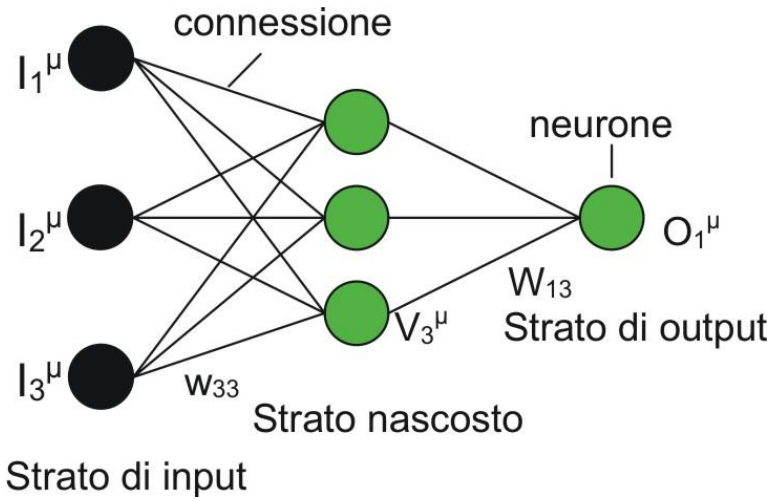
Antonello Pasini[1] · Stefano Amendola[2] · Emmanuel Federbusch[3]

Received: 28 April 2022 / Accepted: 9 September 2022 / Published online: 13 September 2022

Abstract
Is Atlantic Multidecadal Oscillation a genuine representation of natural variability in the climate system? Or perhaps is it strongly forced by external drivers? In this paper, a data-driven attribution investigation has been performed for the Atlantic Multidecadal Oscillation (AMO) behaviour in the past via a machine learning technique, NN modelling. We clearly see a forced nature of AMO in the last 150 years, with a strong contribution of the forcing coming from anthropogenic sulphates, which induces its typical oscillating behaviour. The following original application of our model to future predictions of the AMO behaviour shows that it shall probably lose its oscillating characteristic features. The only way to recover them is to consider an unrealistic increase in anthropogenic sulphates in the future under a strong mitigation scenario, and possibly a low-power solar regime. Due to the established influence of AMO on climate and meteorological phenomena in several regions of the world, our results can be important to better understand the past and envisage several future scenarios.

Lo studio

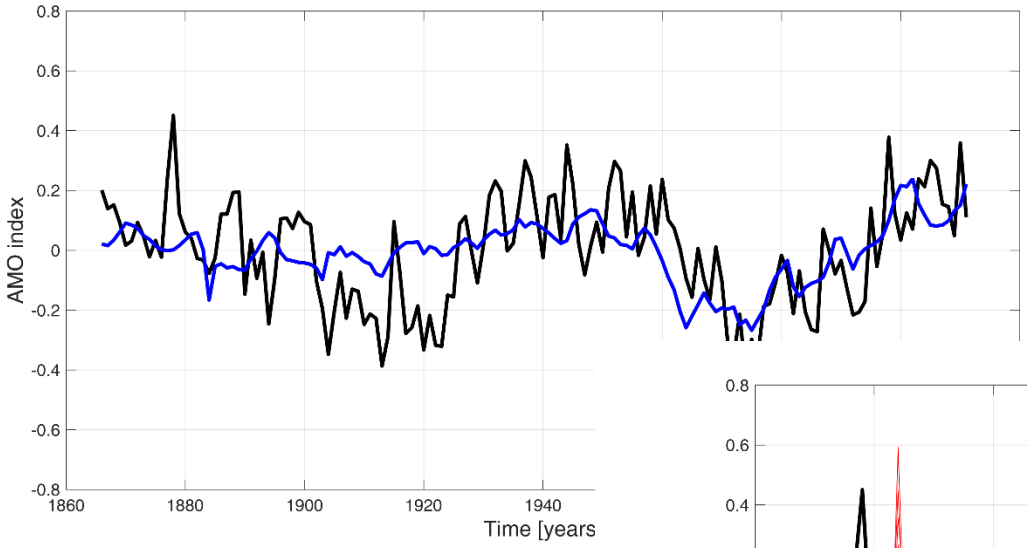
Predittori
RFSOL
RFVOL
RFWARM
RFSOX

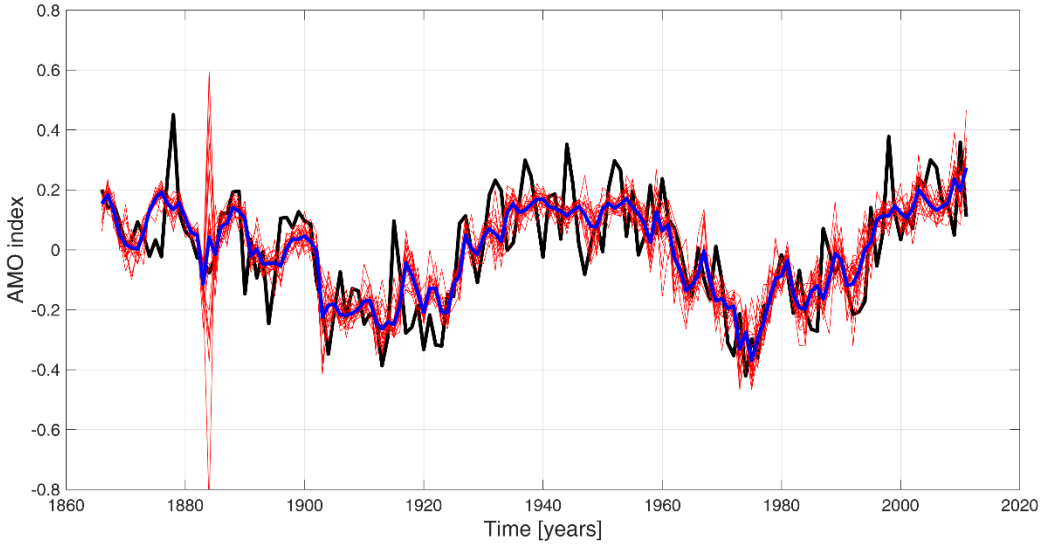


Predittando
Indice AMO

AMO

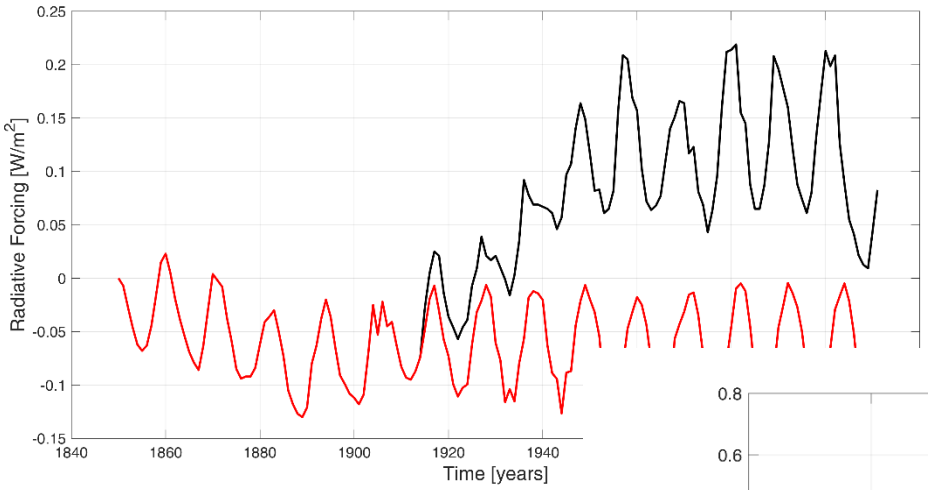
Ricostruzioni lineare e neurale

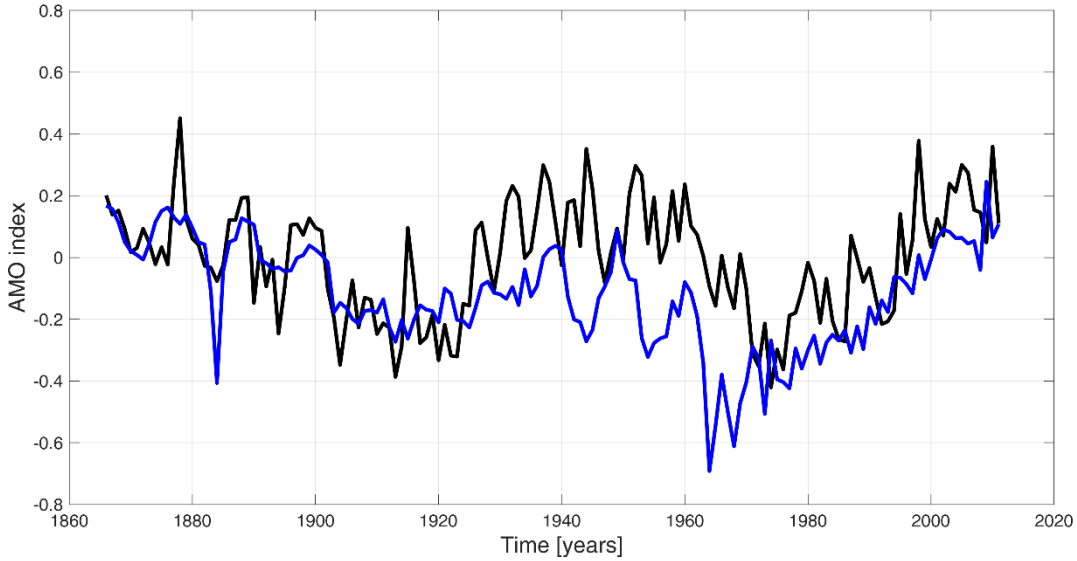




AMO

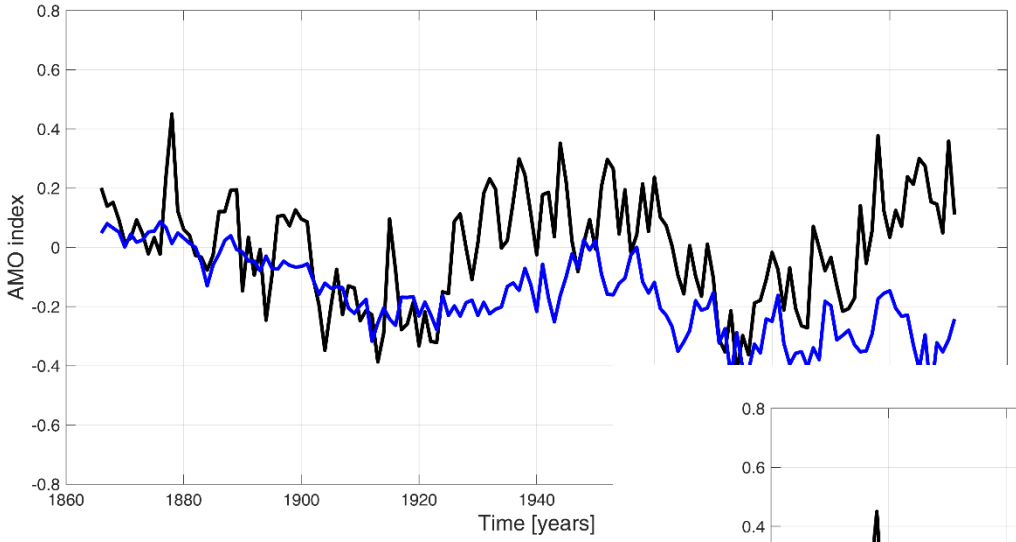
L'influsso del Sole

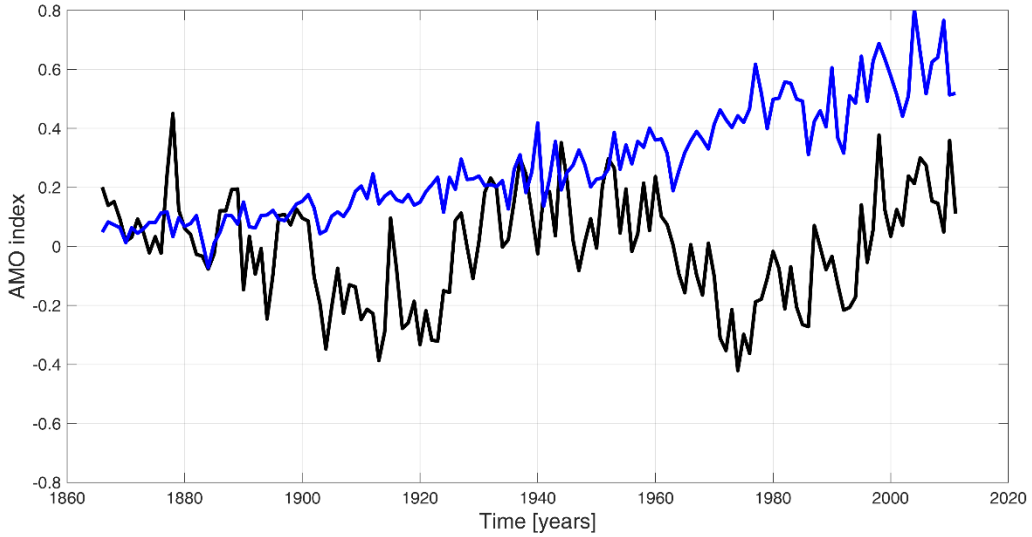




AMO

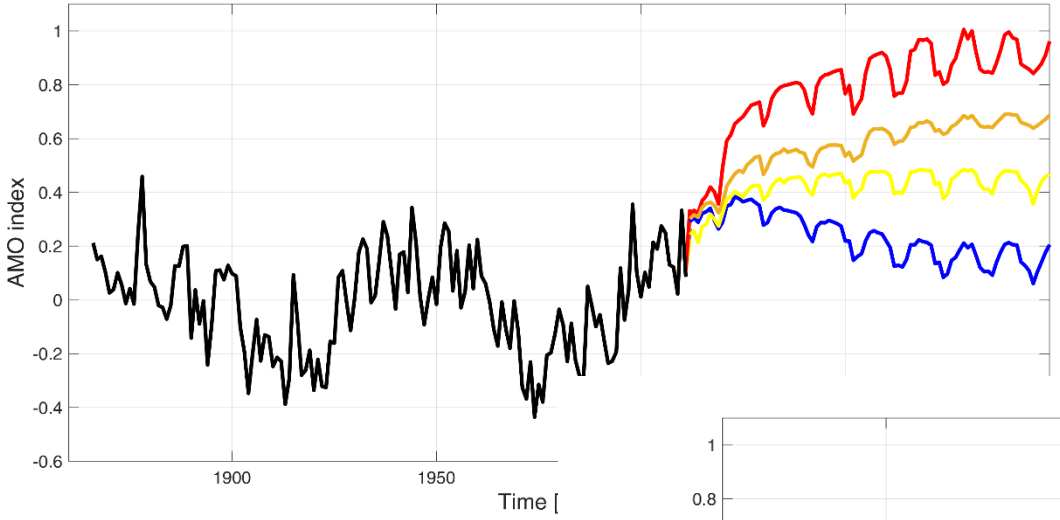
L’influsso dei gas serra e dei solfati

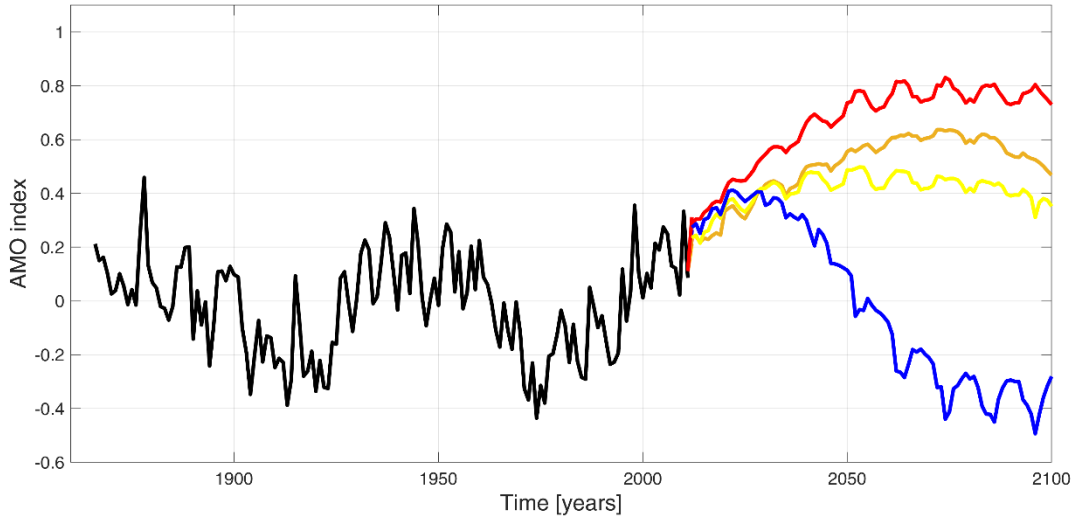




AMO

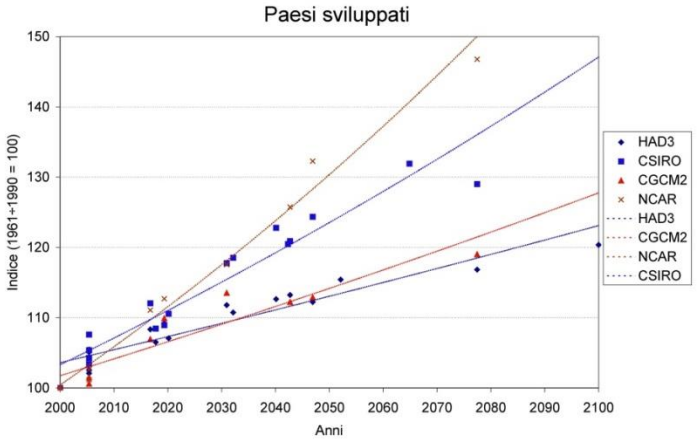
Scenari futuri

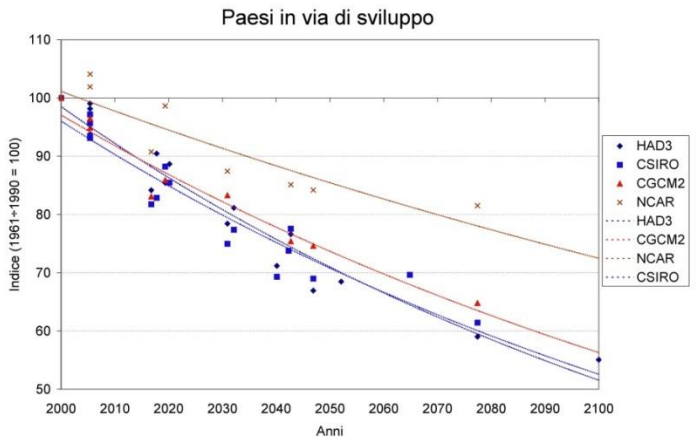


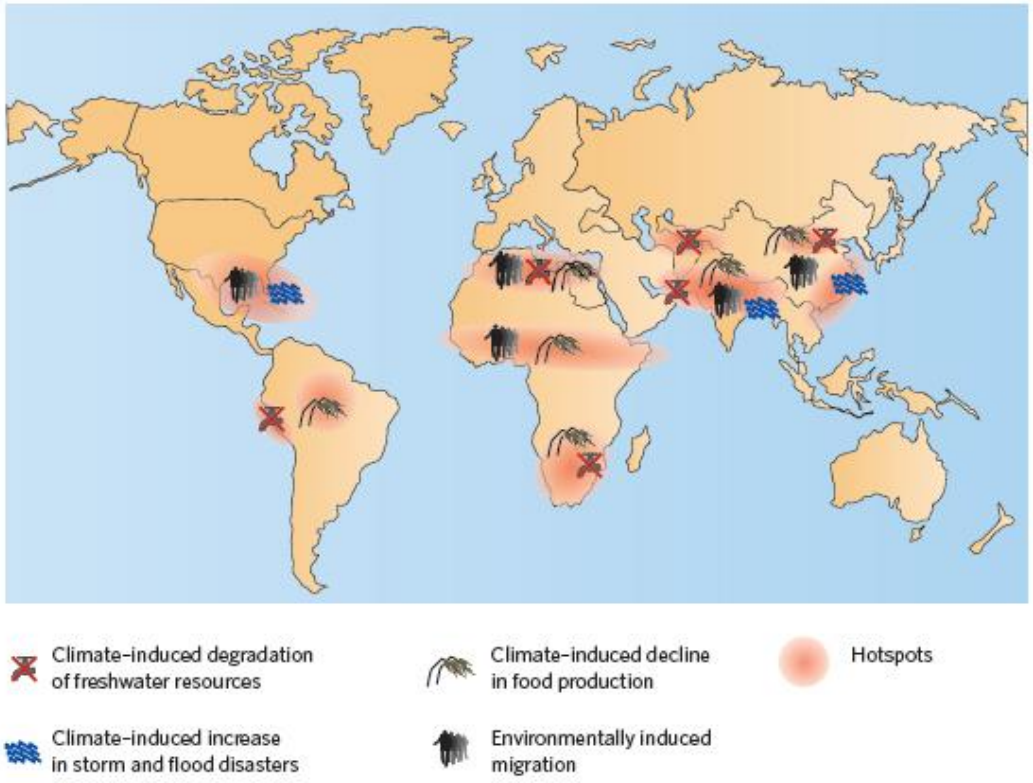


Un impatto del cambiamento climatico

Innesco o concausa di conflitti

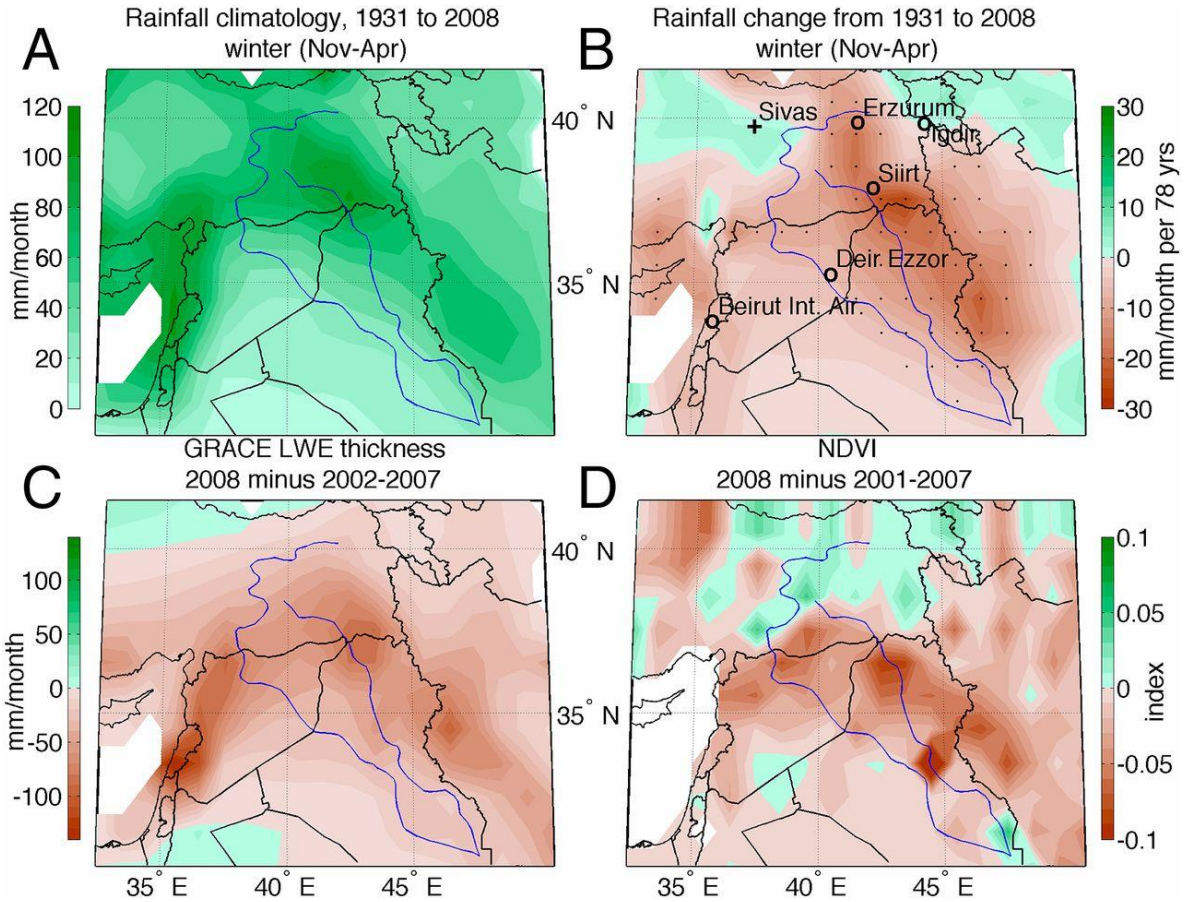






Problemi

Il recente caso della crisi siriana (enorme siccità)



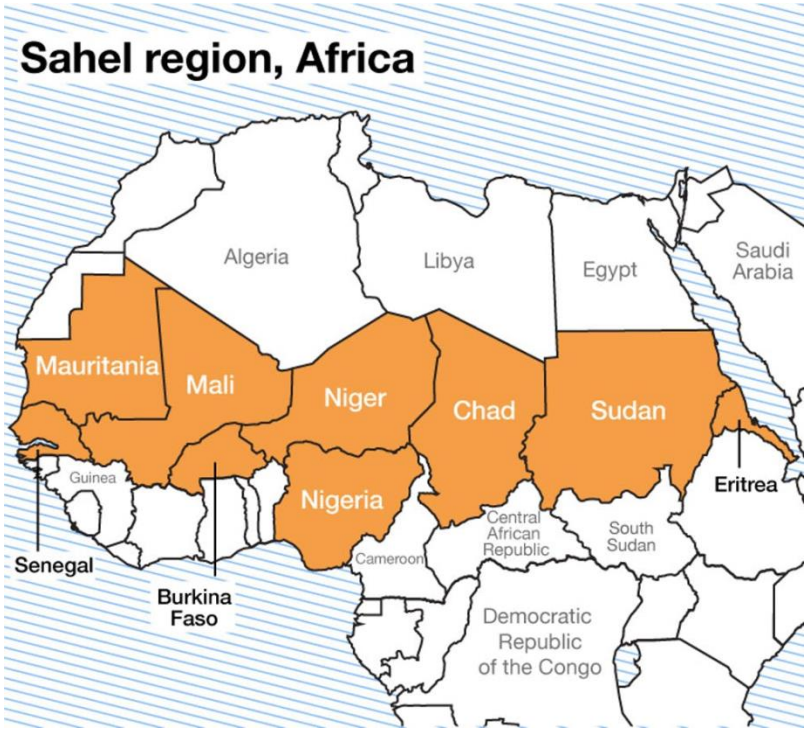
Colin P. Kelley et al. PNAS 2015;112:3241-3246

Problemi

I risultati

Le nostre migrazioni

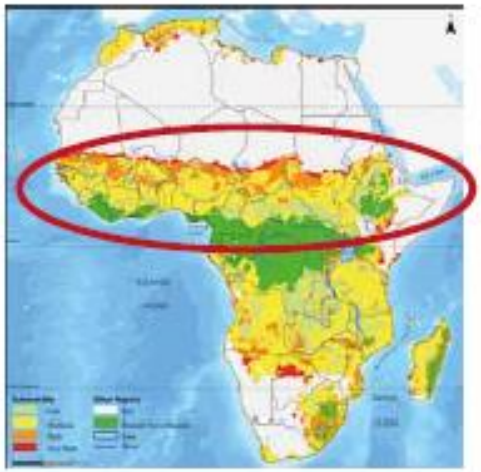
Una zona critica e molto fragile: il Sahel



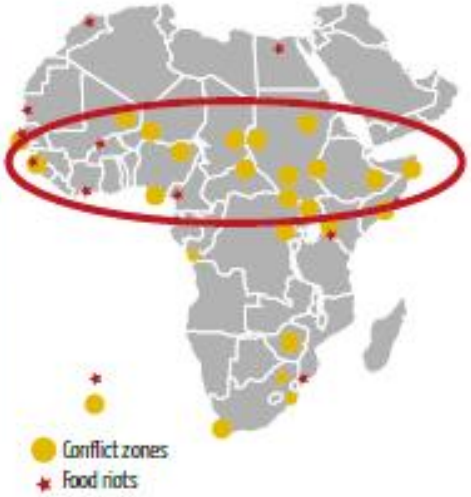
Le nostre migrazioni

Il Sahel è critico da molti punti di vista

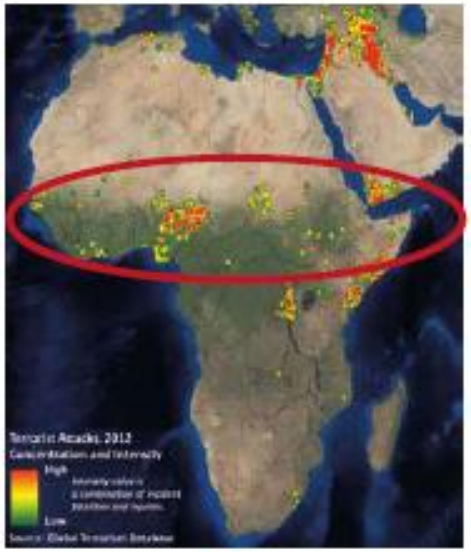
Desertification vulnerability in Africa (2008)



Conflicts and food riots in Africa 2007-2008



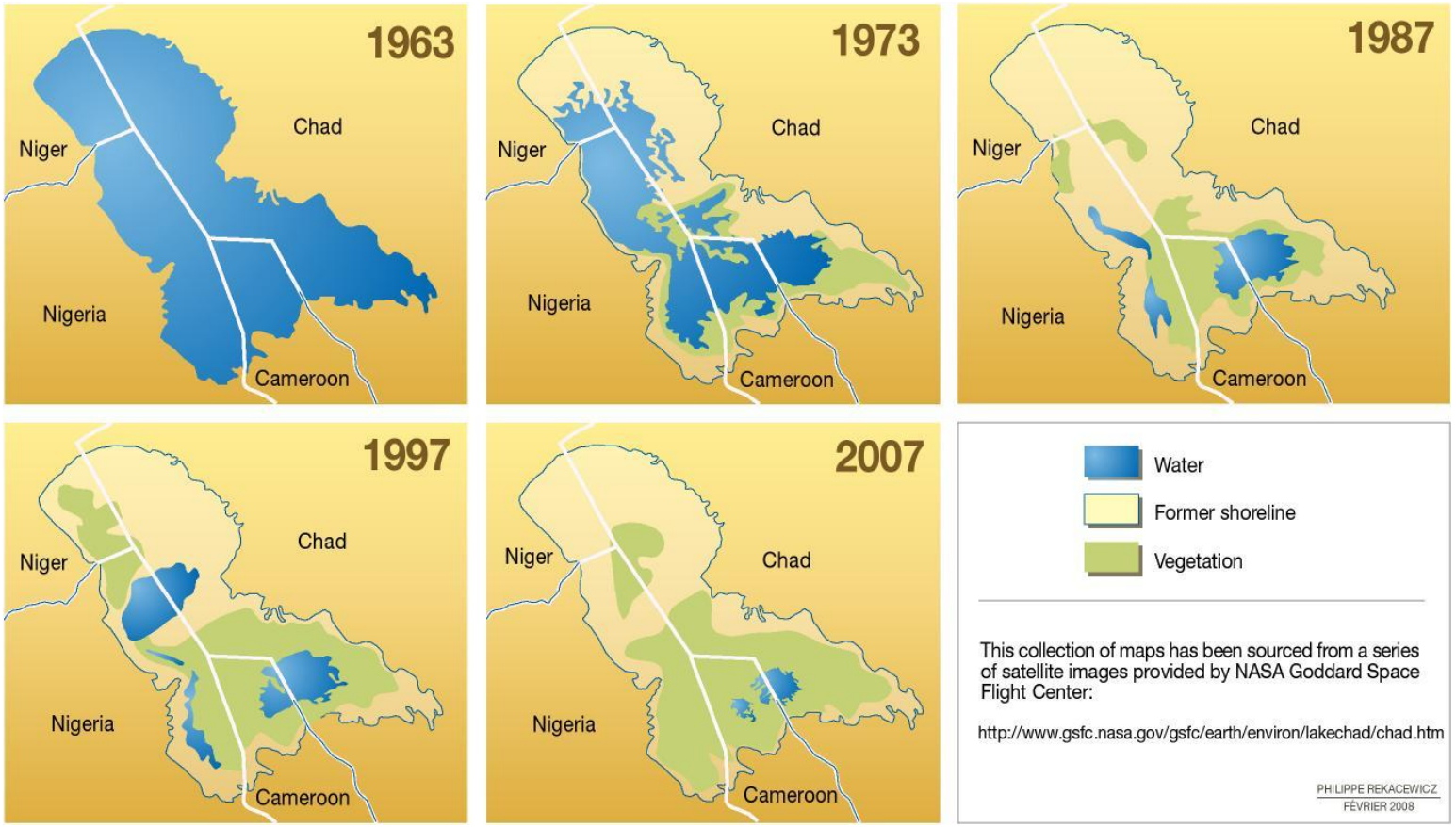
Terrorist Attacks 2012



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.

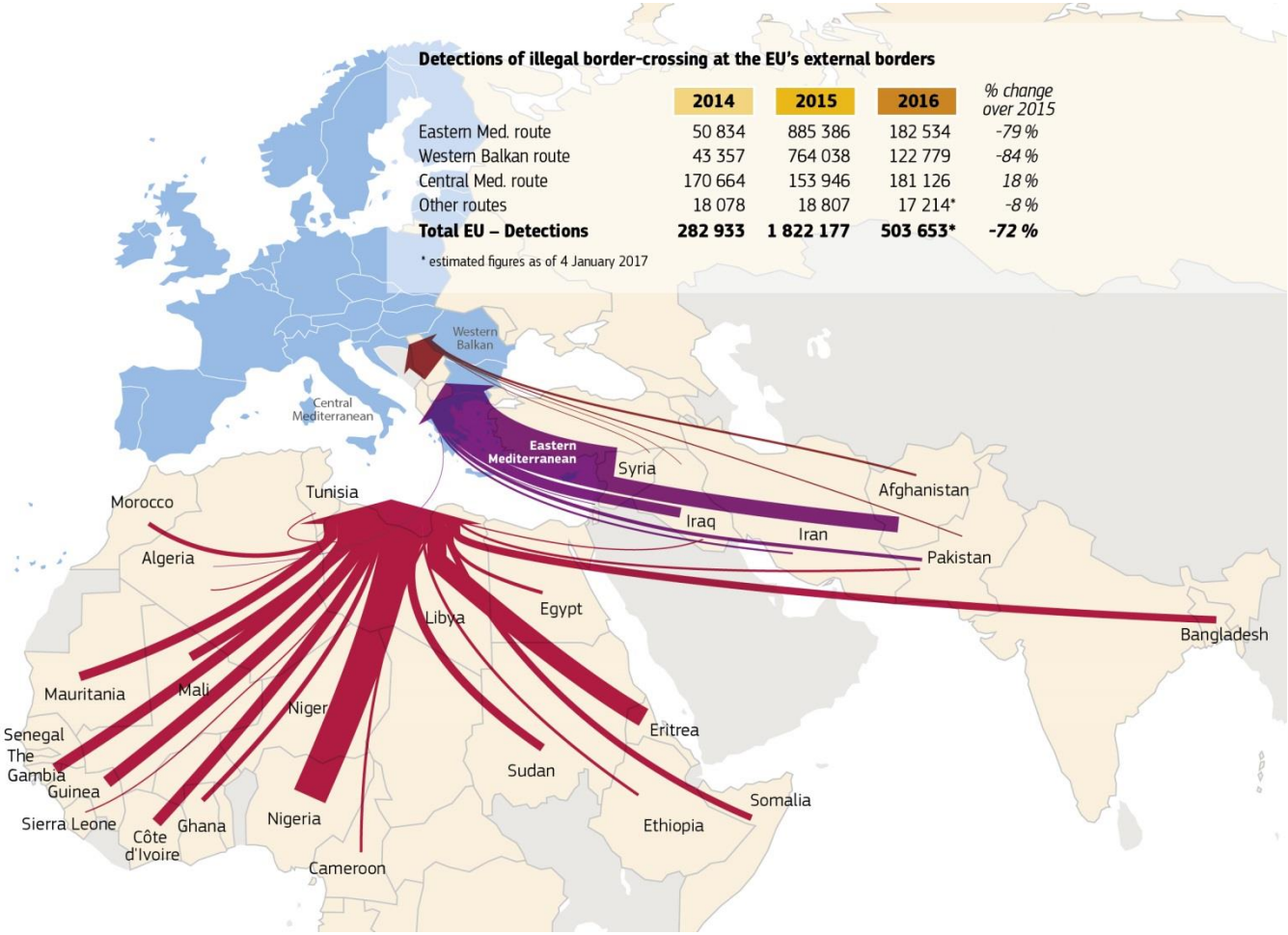
UNCCD, 2014: *Desertification: The Invisible Frontline*

Le nostre migrazioni



Le nostre migrazioni

Il risultato finale



Uno studio specifico

IOP Publishing Environ. Res. Commun. 1 (2019) 011005 https://doi.org/10.1088/2515-7620/ab0464

Environmental Research Communications

LETTER

Linear and nonlinear influences of climatic changes on migration flows: a case study for the 'Mediterranean bridge'

Antonello Pasini[1] and Stefano Amendola[2]

[1] Institute of Atmospheric Pollution Research, National Research Council, Rome, Italy
[2] Department of Mathematics and Physics, Roma Tre University, Rome, Italy

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OPEN ACCESS

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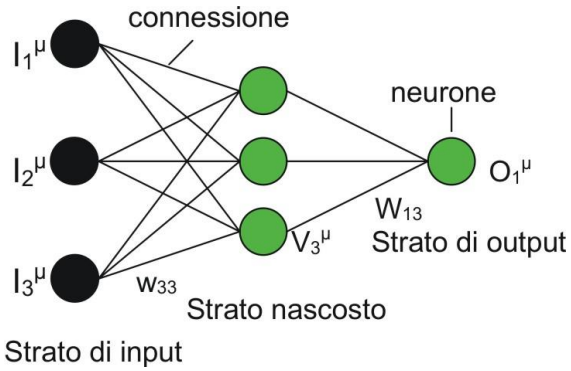
ACCEPTED FOR PUBLICATION 5 February 2019
PUBLISHED 13 February 2019

Keywords: climate-migrations relationship, neural network modelling, climatic causes of migration, nonlinear climatic effects

Supplementary material for this article is available online

Predittori (dati meteo-climatici)

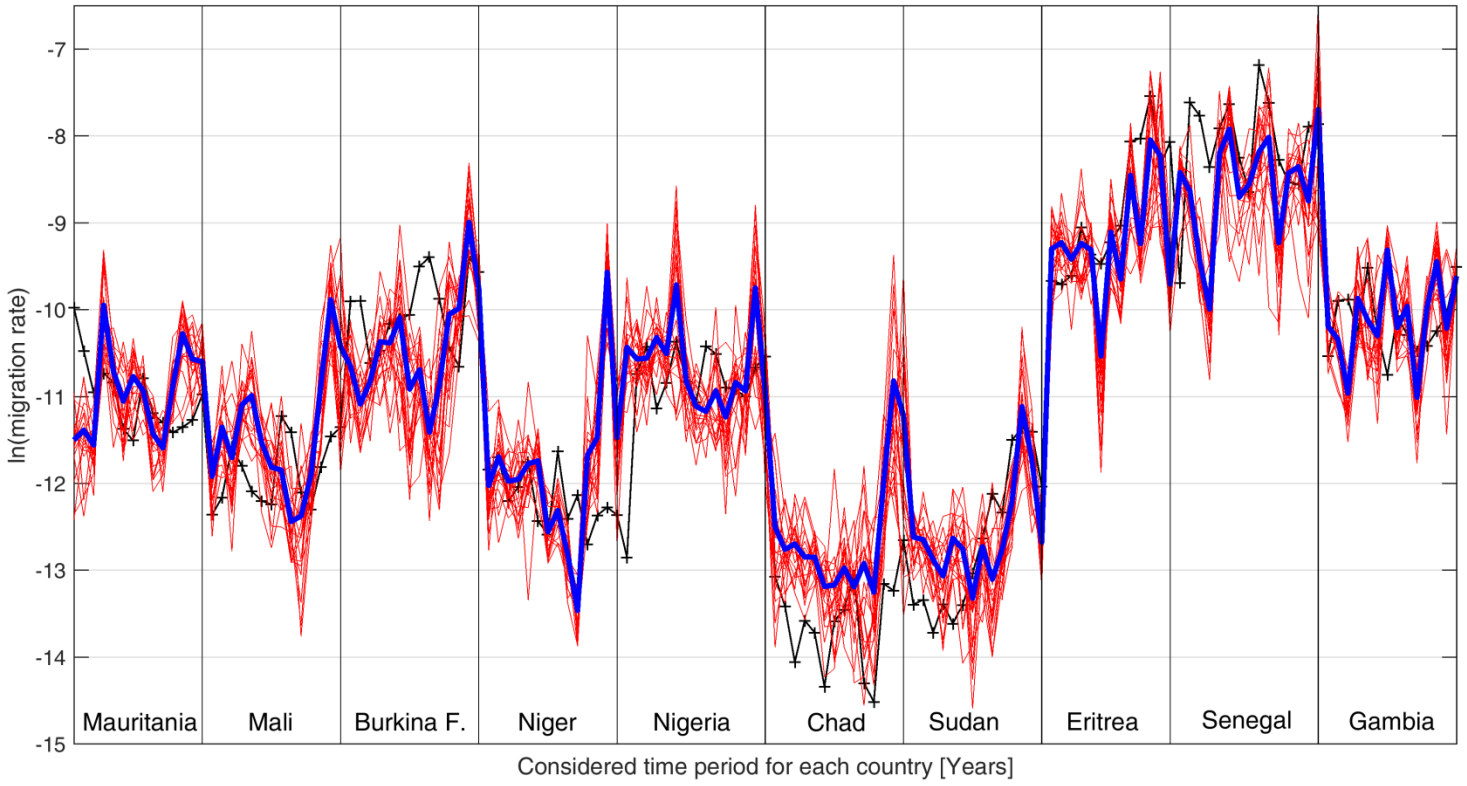


Predittando (flussi migratori)

Risultati principali

Stima dei flussi migratori nel periodo 1995-2009
(predittori: raccolti, temperature, precipitazioni, # ore con T>30°C)

(R^2 = 0.78)



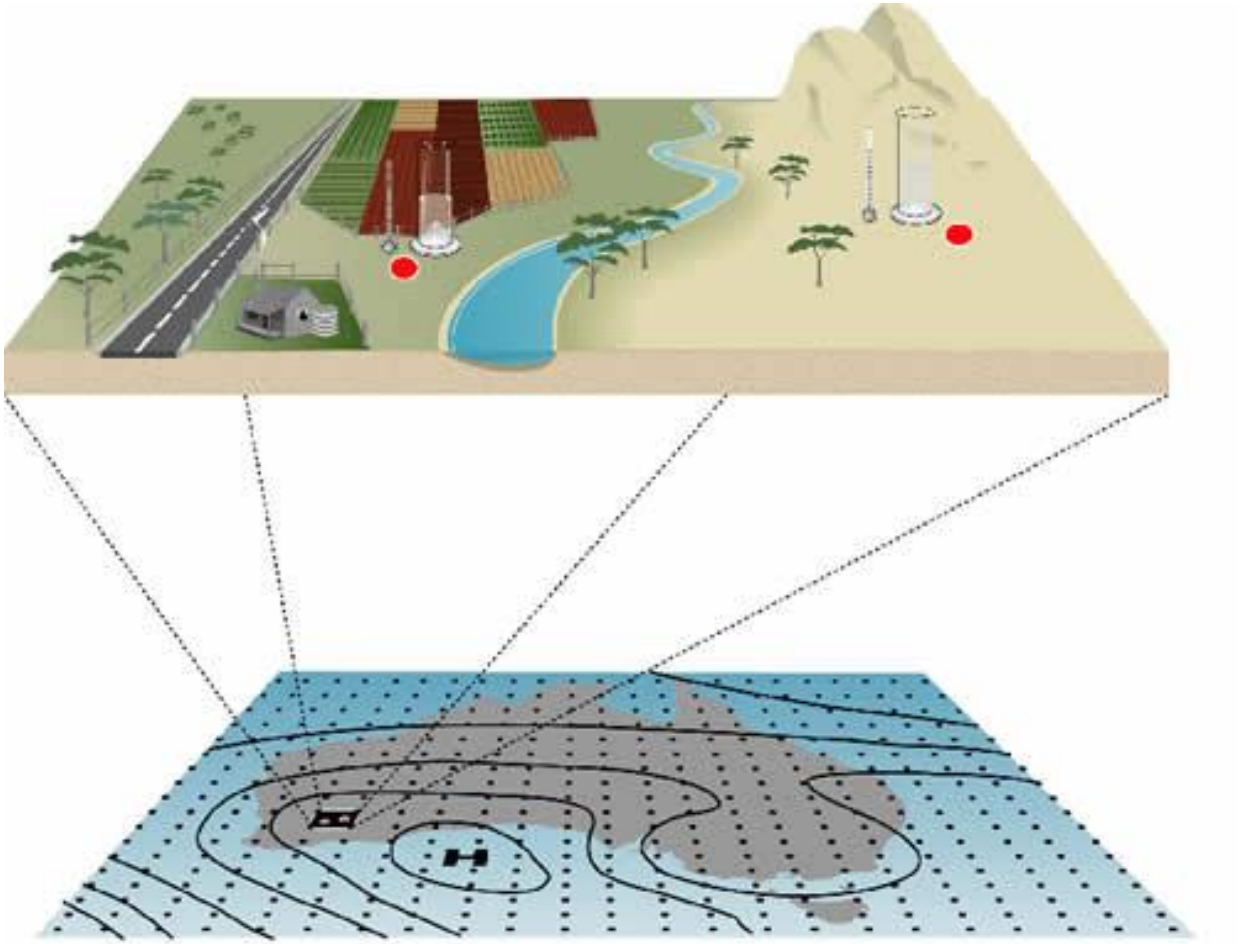
Risultati principali

Tabella per la stima dei flussi migratori

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

I raccolti e il # di ore con T>30°C hanno un chiaro ruolo (non lineare) nell'indurre migrazioni; ciononostante, la temperatura appare essere la variabile più influente. Si sta raggiungendo la soglia della tolleranza fisiologica?

Downscaling

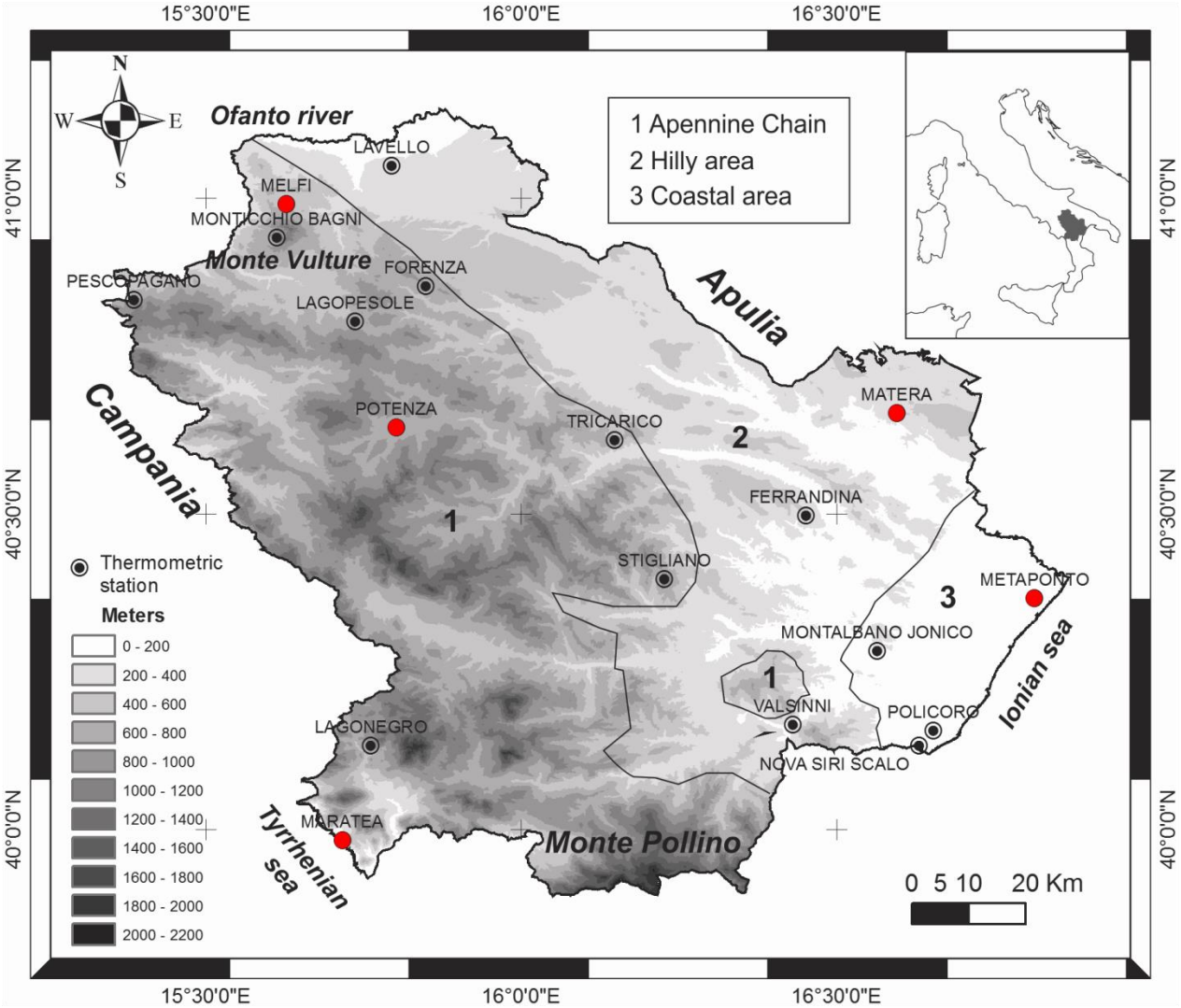


Downscaling

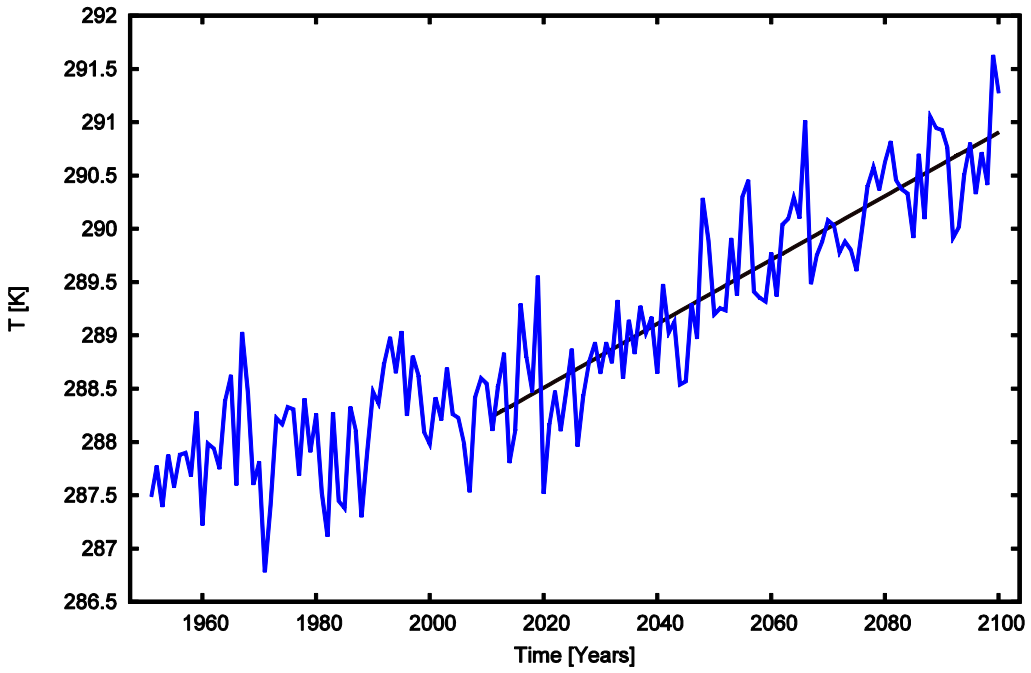
L’idea è quella di utilizzare gli output di ricostruzione nel passato di modelli meteo-climatici per addestrare una rete neurale a ritrovare i valori osservati di alcune variabili su un determinato sito. Poi si applica questo modello neurale a scenari futuri per ottenere scenari climatici locali.

Mostro solo alcuni esempi presi da un progetto di qualche anno fa.

Proiezioni in Basilicata

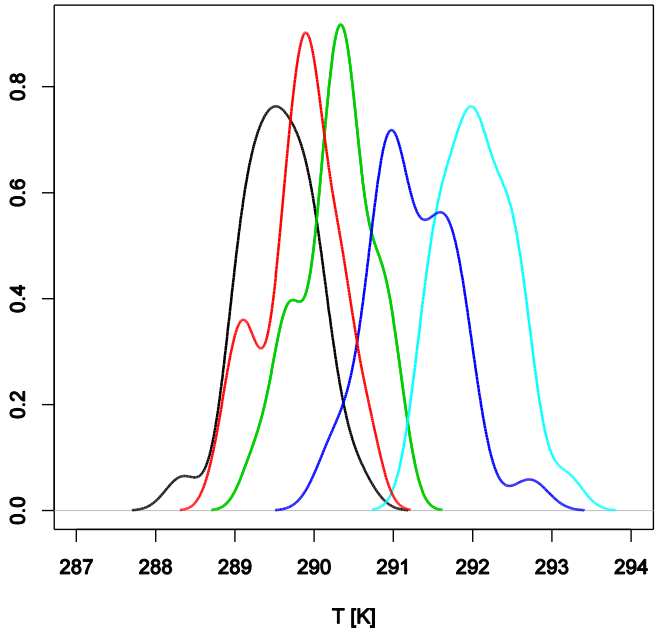


Proiezioni in Basilicata



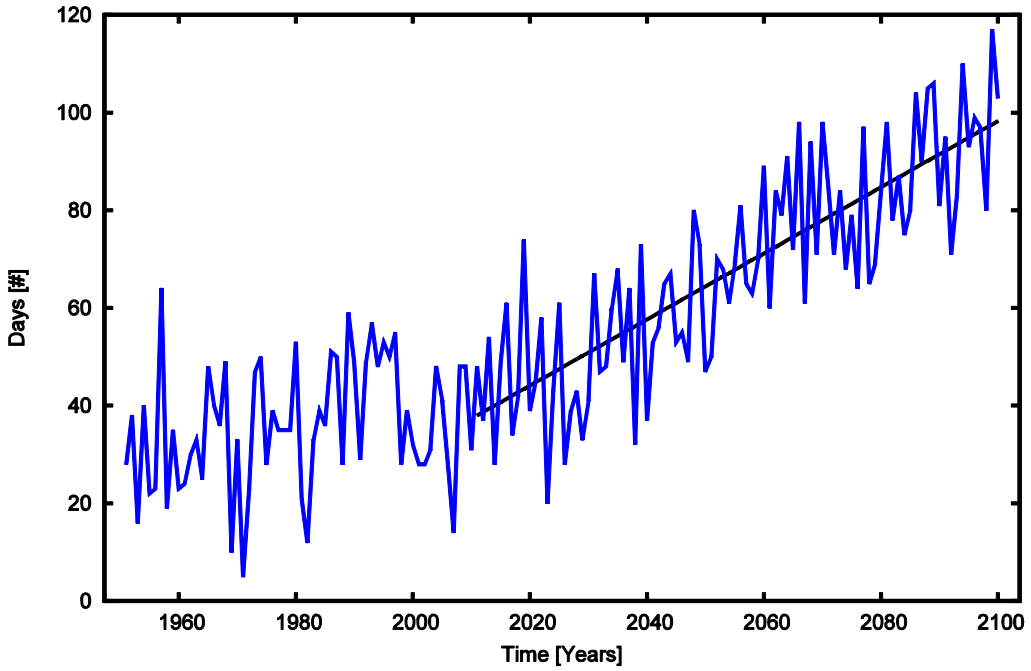
Risultati del modello neurale per le temperature medie annuali a Matera: ricostruite fino al 2010 e previste dal 2011 al 2100. La linea nera mostra il trend dei valori previsti.

Proiezioni in Basilicata



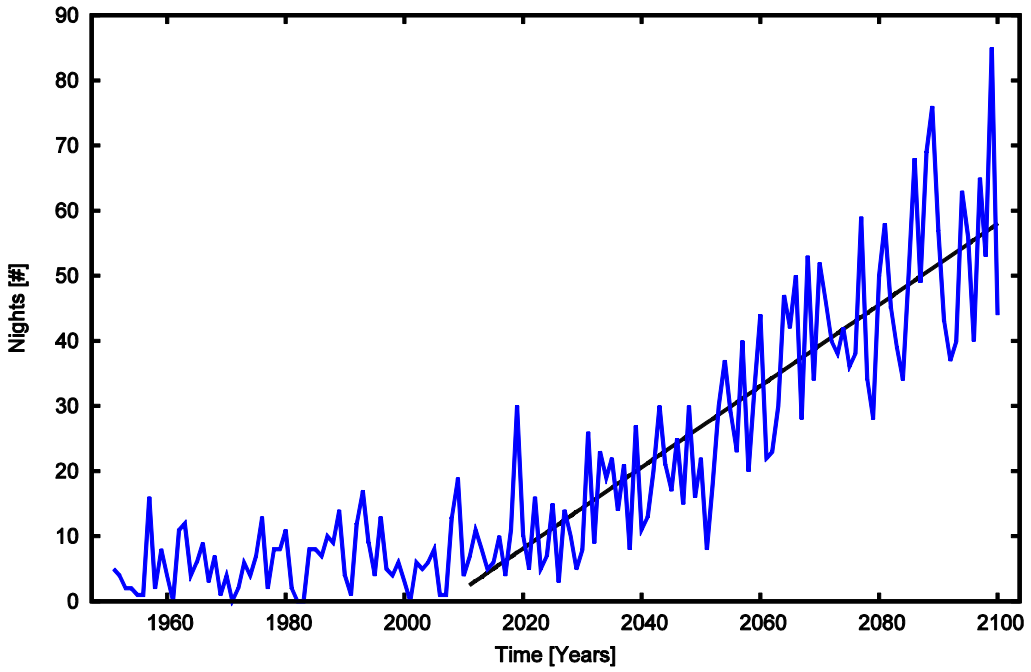
Risultati del modello neurale per la funzione densità delle temperature medie annuali su intervalli di 30 anni a Metaponto: Linea nera: 1951-1980, linea rossa: 1981-2010, linea verde: 2011-2040, linea blu: 2041-2070, linea azzurra: 2071-2100.

Proiezioni in Basilicata



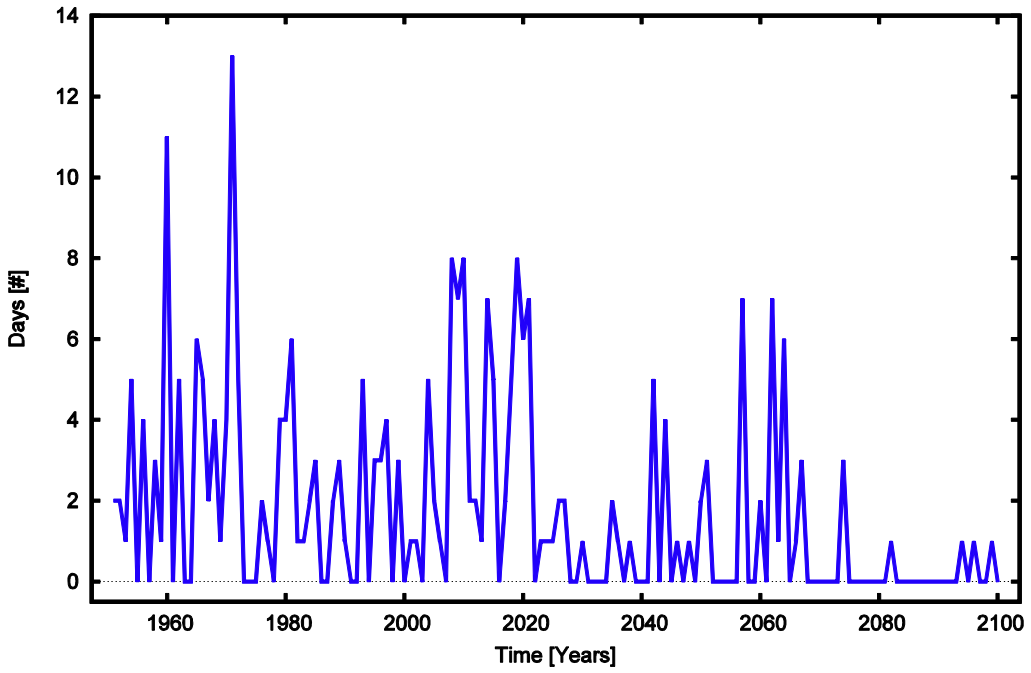
Risultati del modello neurale per il numero di giorni caldi a Maratea: ricostruiti fino al 2010 e previste dal 2011 al 2100. La linea nera mostra il trend dei valori previsti.

Proiezioni in Basilicata



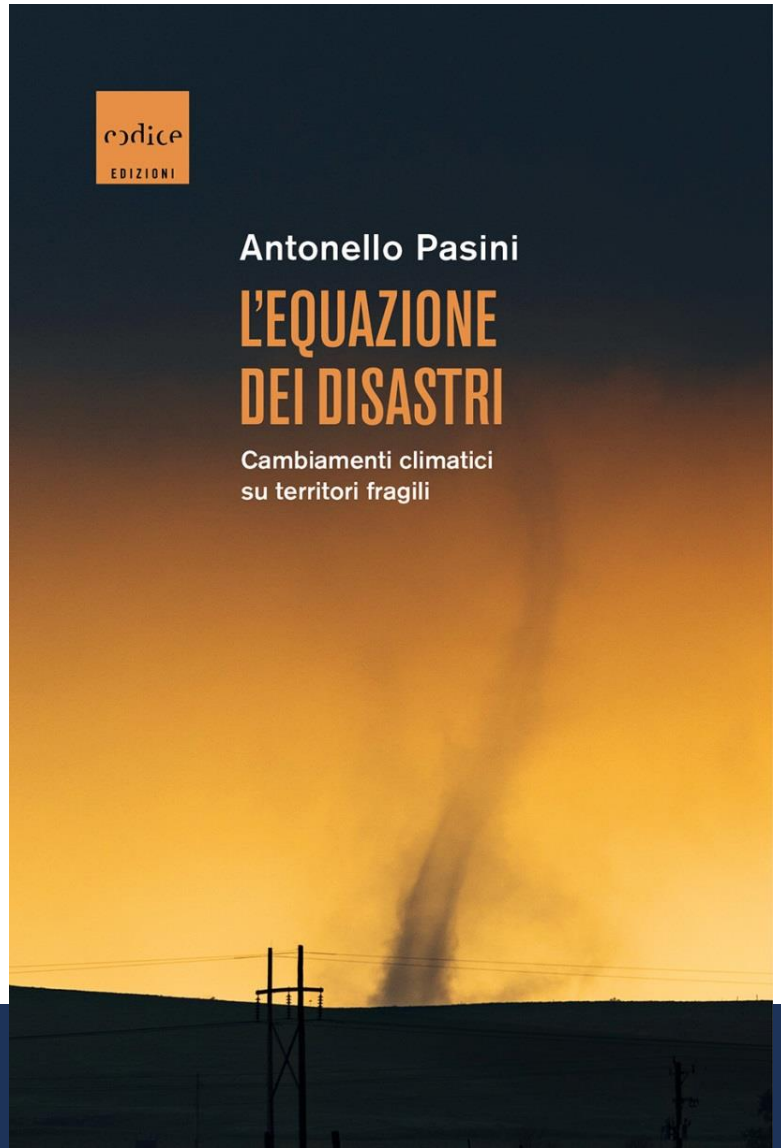
Risultati del modello neurale per il numero di notti tropicali a Melfi: ricostruito fino al 2010 e previsto dal 2011 al 2100. La linea nera mostra il trend dei valori previsti.

Proiezioni in Basilicata



Risultati del modello neurale per il numero di giorni ghiacciati a Potenza: ricostruito fino al 2010 e previsto dal 2011 al 2100.

Due piccoli contributi divulgativi



Anzi, più di due

IL KYOTO FISSO
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