Satellite Earth Observation and AI–QC-Physics methods for enhanced climate predictions and volcano–climate interaction modeling

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Large volcanic eruptions can impact climate, acting as a **forcing** for climate changes. Modeling **Volcano-climate interactions** is difficult, due to the **inherent complexity of the interrelationships**.

Advanced Computing Technologies, in particular with Artificial Intelligence (AI) approaches and Quantum Computing (QC), can improve the modeling of these interactions:

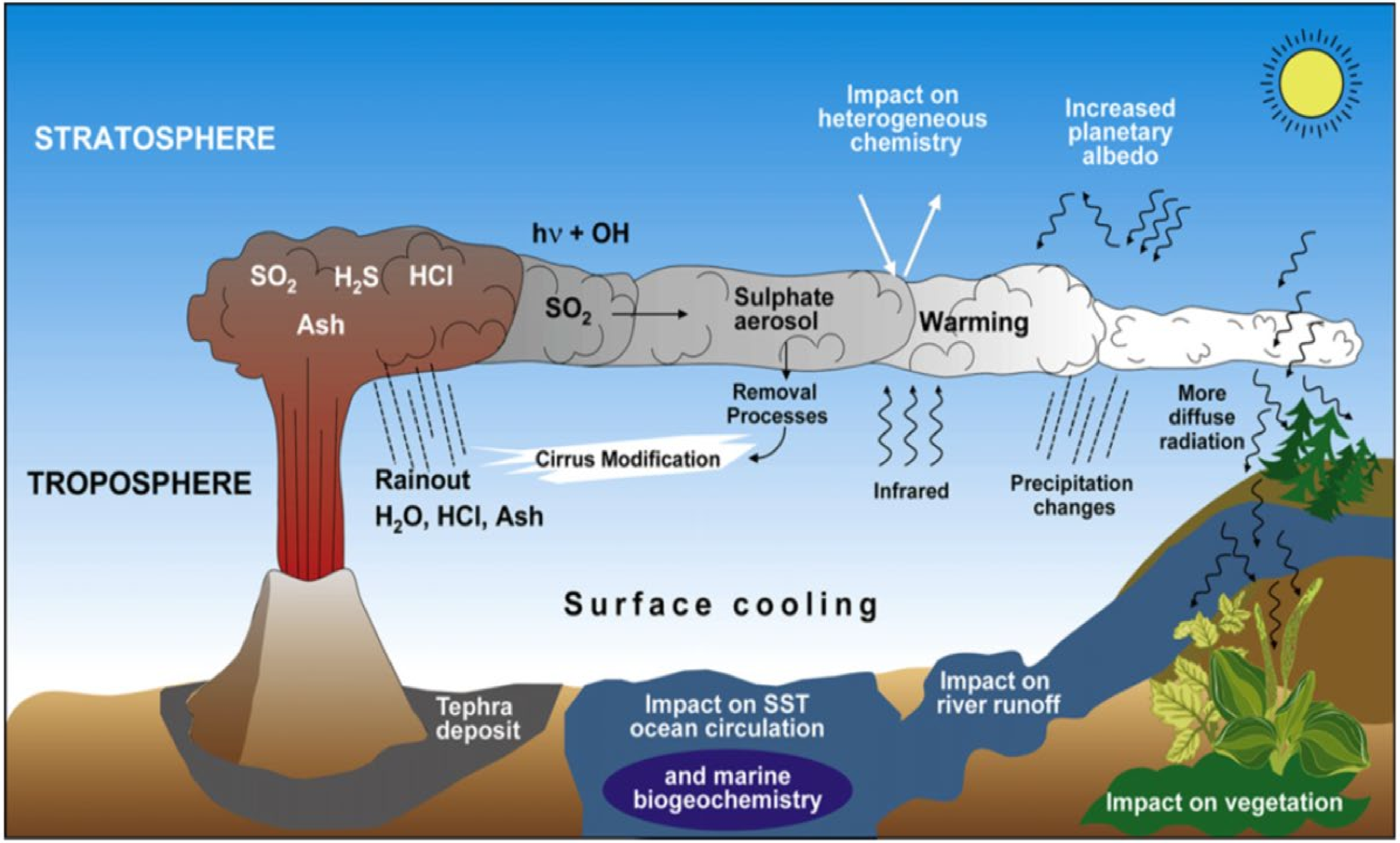
- **unveiling hidden patterns,**
- **deeper understanding the specific phenomenology,**
- **improving** and **speeding-up** the predictions

Tambora eruption, 1815
Source: https://it.geologyscience.com/

1816 was *the year without summer*

Krakatoa eruption, 1883. Source: https://it.geologyscience.com/

Phenomenology



Source: Timmerek et al., 2010

Framework

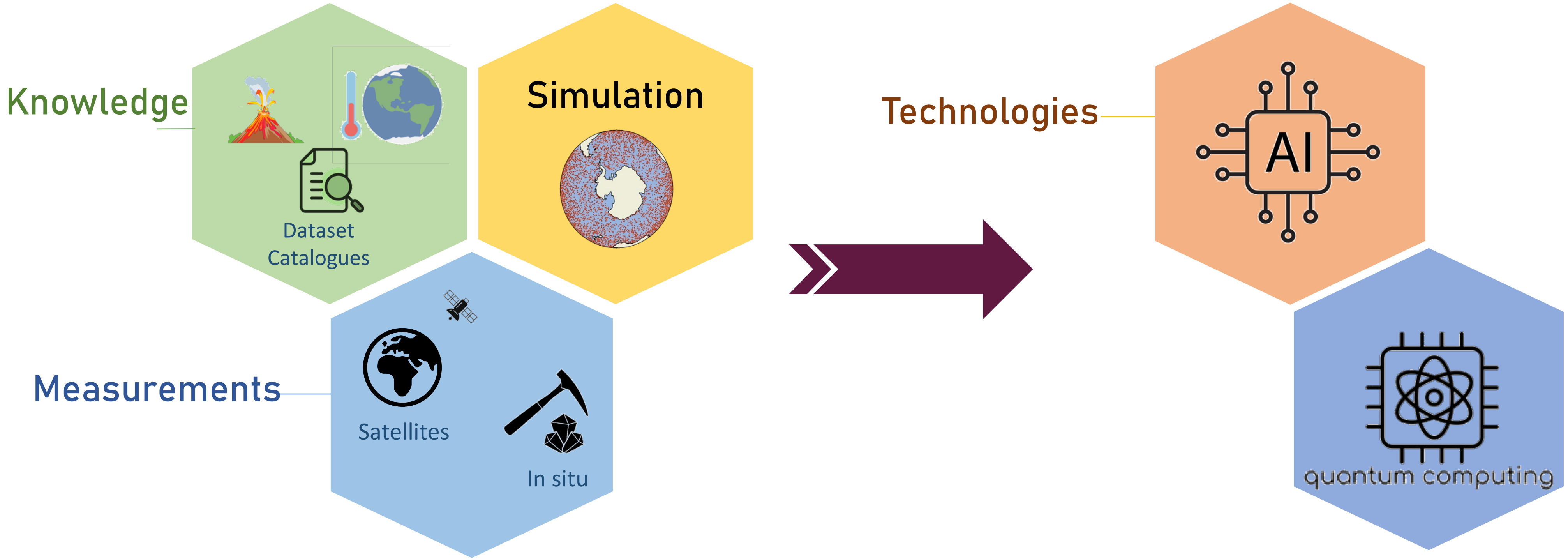
Investigate the Volcano-Climate interactions through:

- Enhanced Modeling
- Earth Observation

We leverage recent advancements in **Artificial Intelligence (AI)** and **Quantum Computing (QC)** to enhance the descriptive accuracy of climate-volcano interactions.

Objectives:

- Deeper understanding of the interaction mechanisms
- Forecasting capabilities



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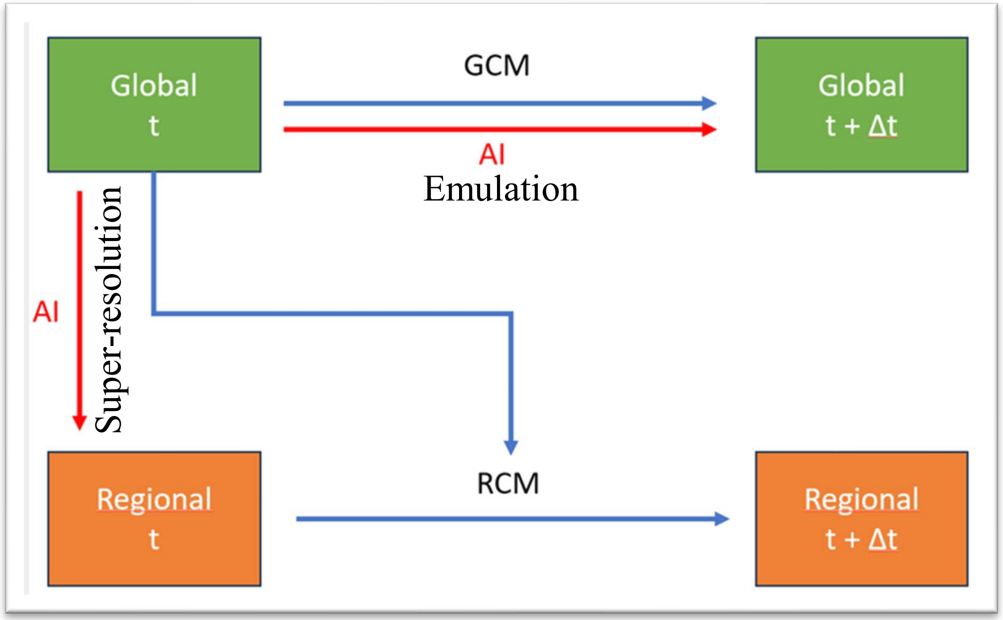
Methodological framework

1) AI-based **super-resolution** approaches to enhance the spatial resolution of global climate simulations: **Deep Learning (DL) architectures** to map low resolution reanalysis ECMWF ERA5 images into high resolution ones, focusing on the temperature at 2 meter [Amato et al. 2025a; Zago et al. 2025a; Zago et al. 2025b]

2) AI-based **emulators** for climatic models: AI-based models to reproduce **climatic models**, applied to volcanic activity, to investigate the impact on climatic changes [Amato et al. 2026a; Amato et a. 2025b; Amato et al. 2025c, Basile et al. 2026]

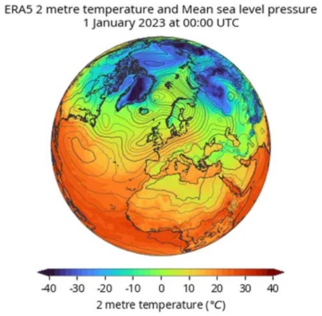
General framework

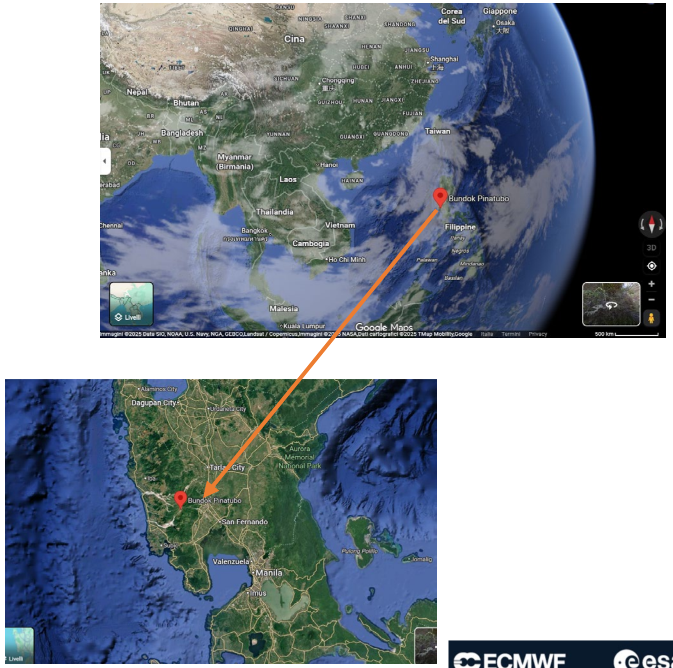


Case study

1991 eruption of Mount Pinatubo, the second-largest volcanic eruption of the 20th century, in the satellite era. This represents an ideal case study, as it was sufficiently large to have some climatic impacts, and it is relatively recent, so well observed.

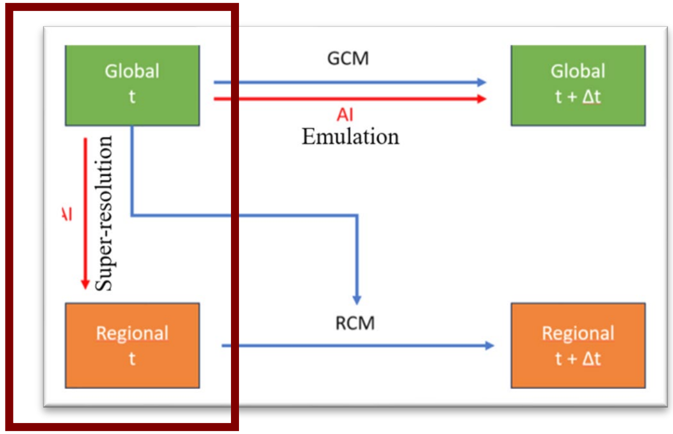
DATA: **ECMWF - ERA5 reanalysis**, hourly data on single levels
VARIABLES: ["**t2m**"] – temperature of air at 2m above the surface of land, sea or inland waters, in kelvin (K). It is calculated by interpolating between the lowest model level and the Earth's surface, taking account of the atmospheric conditions
https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview





1) Super-resolution with enhanced technologies

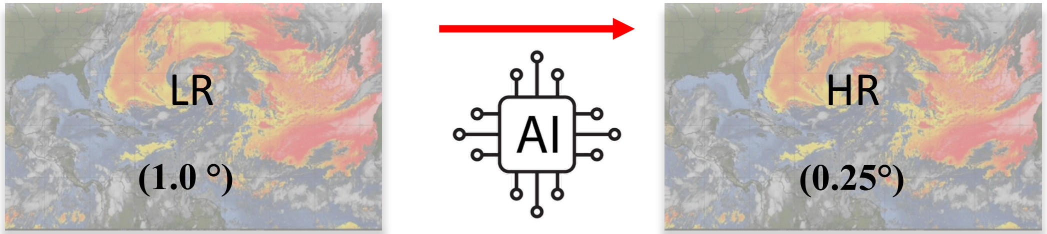
Super-Resolution (SR) is the process of recovering a high-resolution (HR) functional state from a corresponding low-resolution (LR) observation, treating climate data (e.g., temperature or precipitation grids) as digital images and applies neural networks to reconstruct high-frequency details → non-linear NNs



AI approaches, trained and tested on **ERA 5** reanalysis data:

- ResNet,
- RNN,
- ConvRNN

→ + Fourier layers
+ Quantum layers



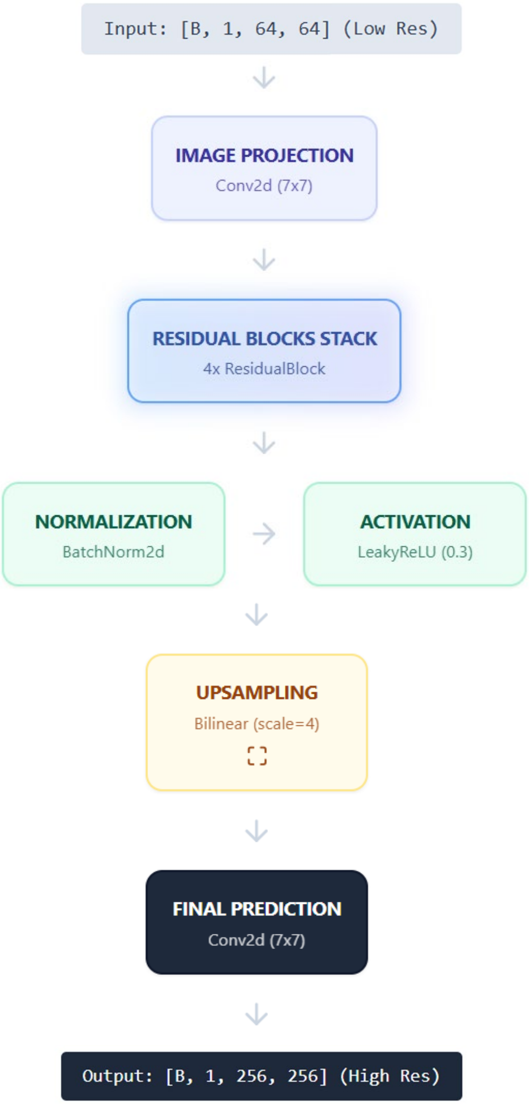
Learning parameters	
Metrics used for quantitative evaluation	MSE (Mean Squared Error), MAE (Mean Absolute Error), SSIM (Structural similarity index measure)
Loss	0.4*MSE+0.6*MAE
Early stopping technique	Maximum: 1000, Patience: 20
Learning rate	1e-4

Data used (01/01, 01/04, 01/07, 01/10 00:00 for each year)	
Training set	2001, 2003, 2005
Validation set	2002
Test set	1992, 1990-2010

Maraun, D., & Widmann, M. (2018). *Statistical Downscaling and Bias Correction for Climate Research*. Cambridge University Press; Vandal, T., et al. (2017). "DeepSD: Generating High Resolution Climate Change Projections through Single Image Super-Resolution". Proceedings of the 23rd ACM SIGKDD

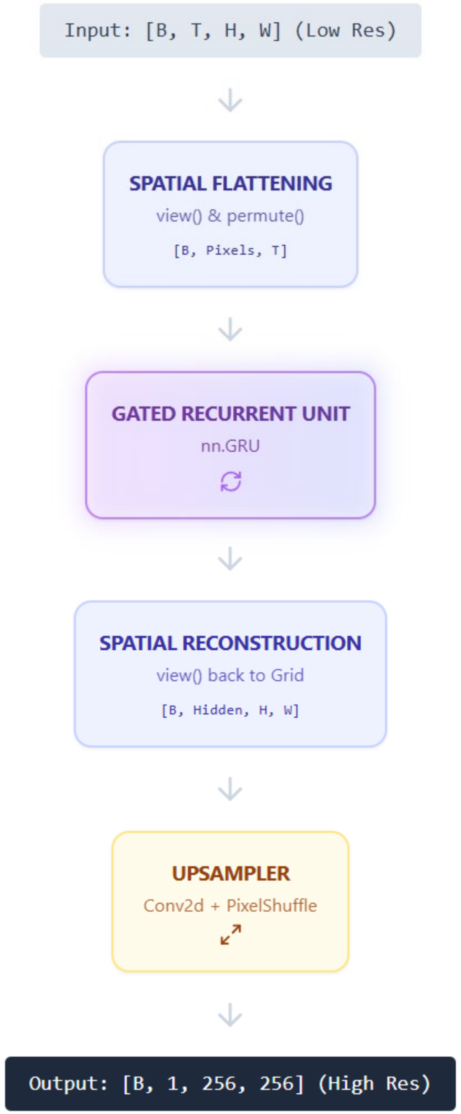
AI super-resolution architectures

ResNet



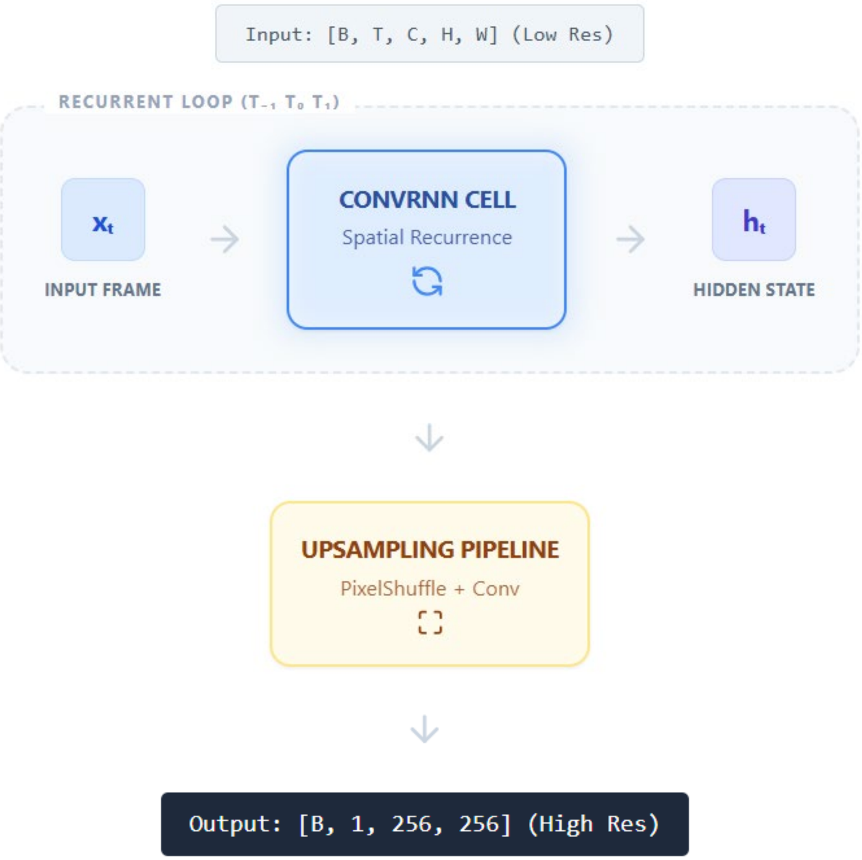
Reconstructing high-resolution details based only on the spatial distribution of pixels

RNN



Temporal coherence and intrinsic thermal inertia

ConvRNN



Spatio-temporal evolution

He et al., 2016; Ledig, C., et al. (2017); Cho, K., et al. (2014); Ballas, N., et al. (2016)

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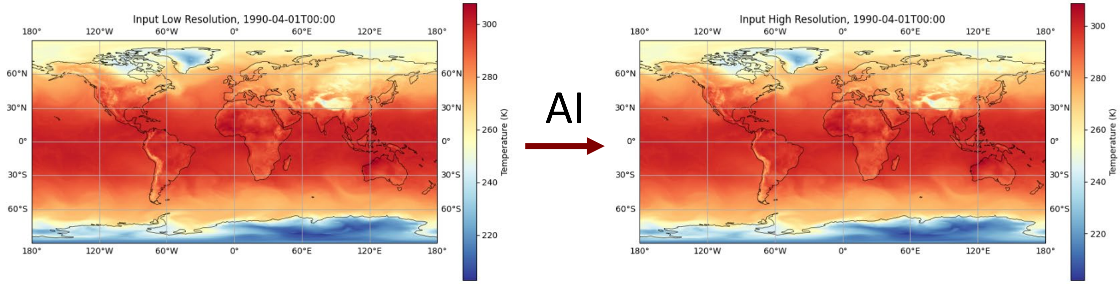
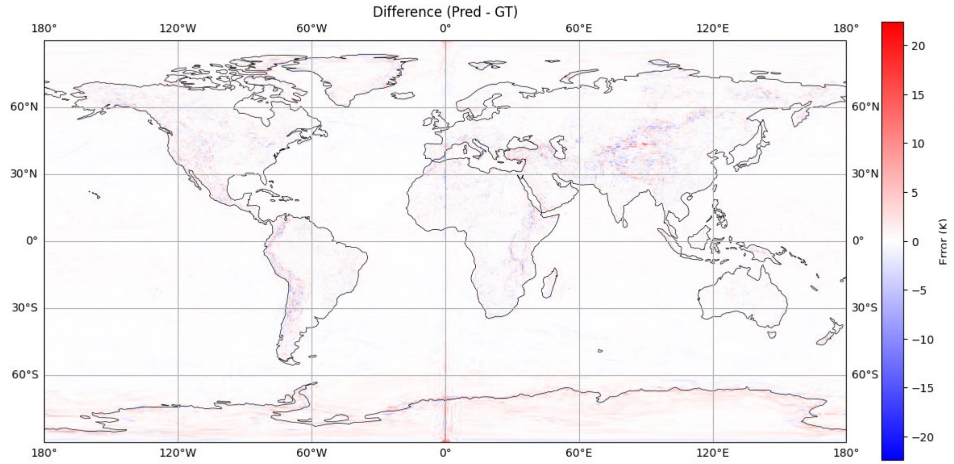
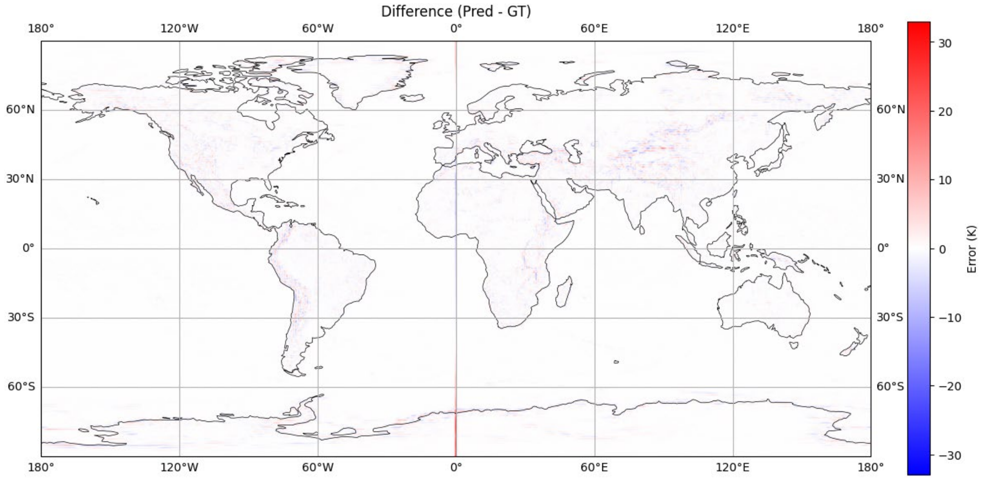
AI models with advanced technologies: super-resolution results, difference between ground truth and prediction





ResNet

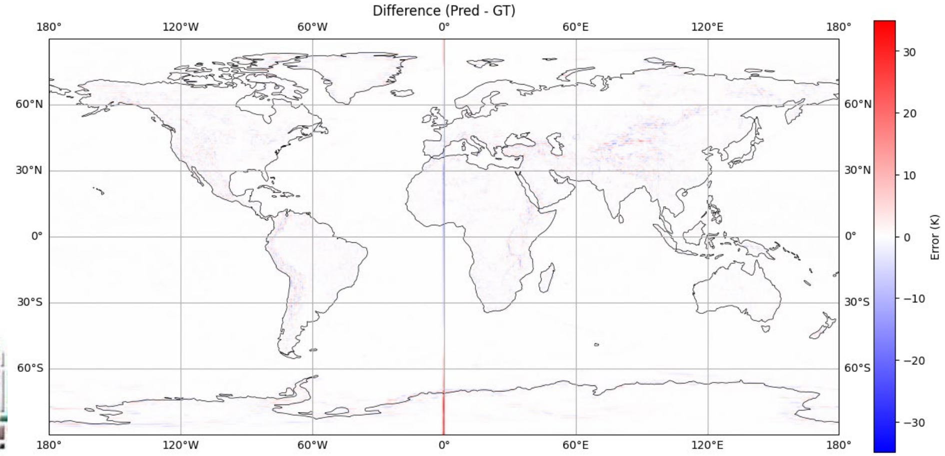


RNN

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$



ConvRNN

MSE and MAE are "error" measurements, so they have to be close to 0, SSIM is a similarity index, so it has to be close to 1

	MSE (K^2)	MAE (K)	SSIM ([-1,1])
ResNet	0.66	0.438	0.977
RNN	**0.572**	0.304	0.98
ConvRNN	0.614	**0.299**	**0.981**

Models performances comparison

ConvRNN has better performances in catching spatio-temporal dynamics

Amato et al., 2026 (in prep.)

ECMWF esa

AI super-resolution models: ConvRNN with advanced layers

To process global patterns, we can introduce Fourier or Quantum layers:

- Test 1

SPECTRAL CONV 2D
Fourier domain

SpectralConv2d is the frequency domain equivalent of a convolutional layer (ConvRNN), it looks small squares of pixels.
Decomposing the image into Fourier frequences (modes), Fourier layer looks **entire image at once** to find **global patterns, preserving local details:** low frequencies represent large-scale structures (global climate signal, atmospheric circulation), high frequencies represent local details and noise
Resolution invariance: Zero-shot Super Resolution

Li, et al., (2020)

- Test 2

SAMPLER QNN
2-qubit circuit

The quantum layer (QNN) acts as a **nonlinear refiner** of the features extracted by the ConvRNN. Data transformed into the Hilbert space of qubits, quantum layer takes hidden state, maps it via the **embedding** (**e.g.,** ZZFeatureMap) and processes it with the **ansatz** (EfficientSU2). **2-qubit quantum circuit** to analyze time series: here, **global averaged temperature**.
Quantum expressivity: complexity amplifier, non-linear (and non-local) correlations, reduced parameters, better uncertainties modelling

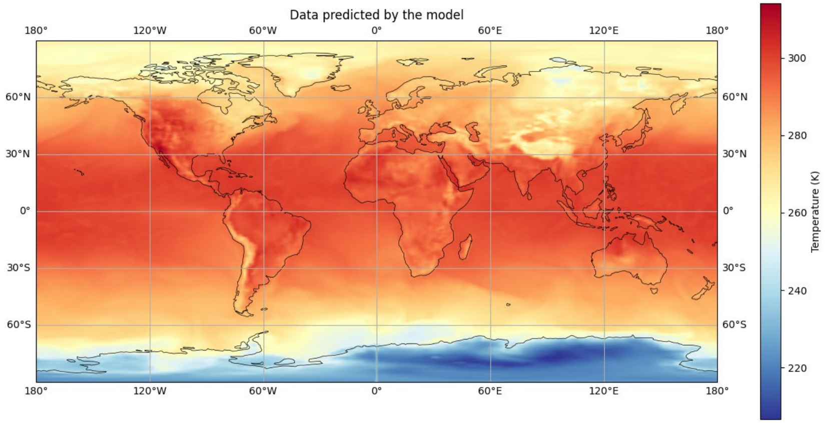
with **Qiskit AerSimulator**, noisy quantum circuit simulator backend

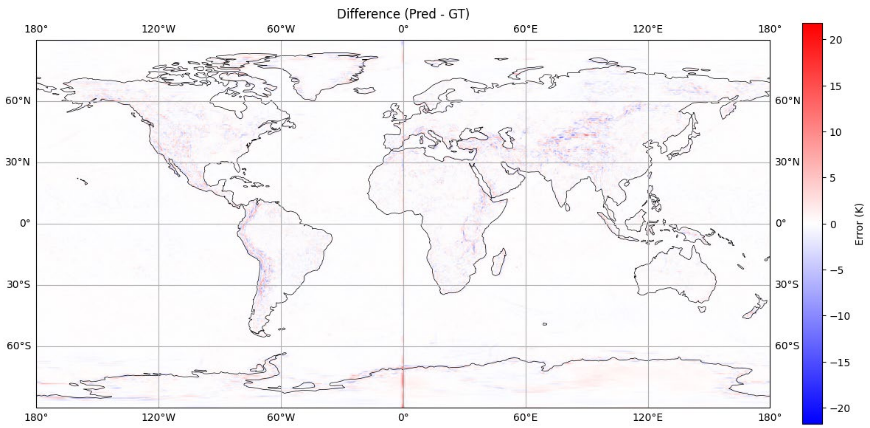
Qiskit

Abbas, A., et al. (2021); Mari et al., (2020)

AI models with advanced technologies: super-resolution results

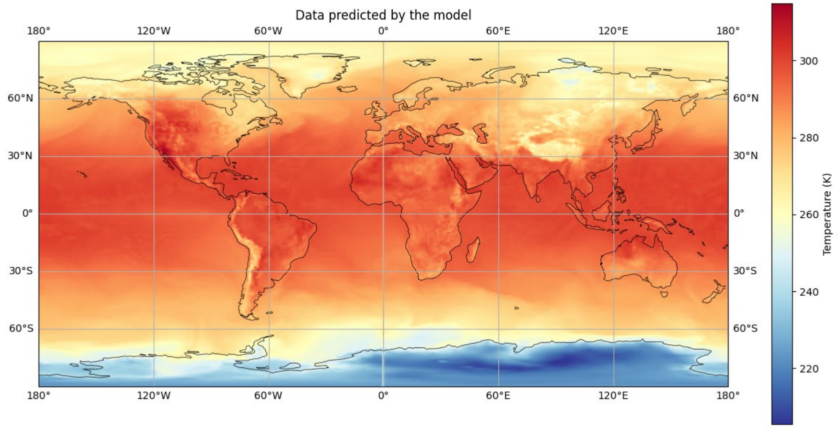
- Test 1: ConvRNN+Fourier

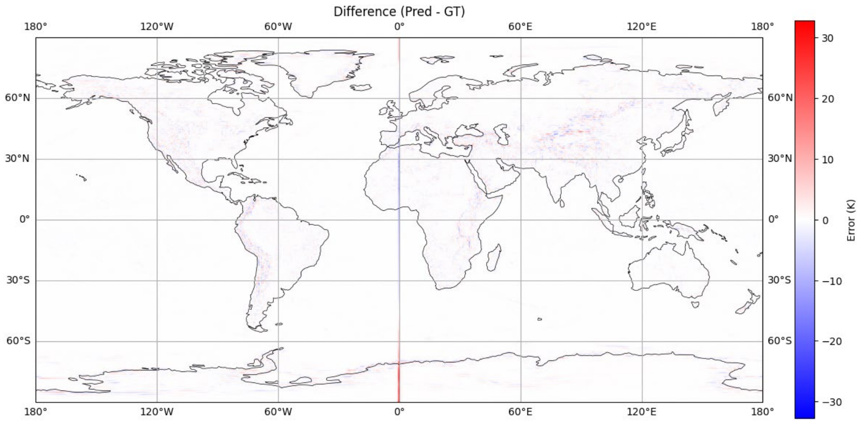




SPECTRAL CONV 2D
Fourier domain

- Test 2: ConvRNN+Quantum



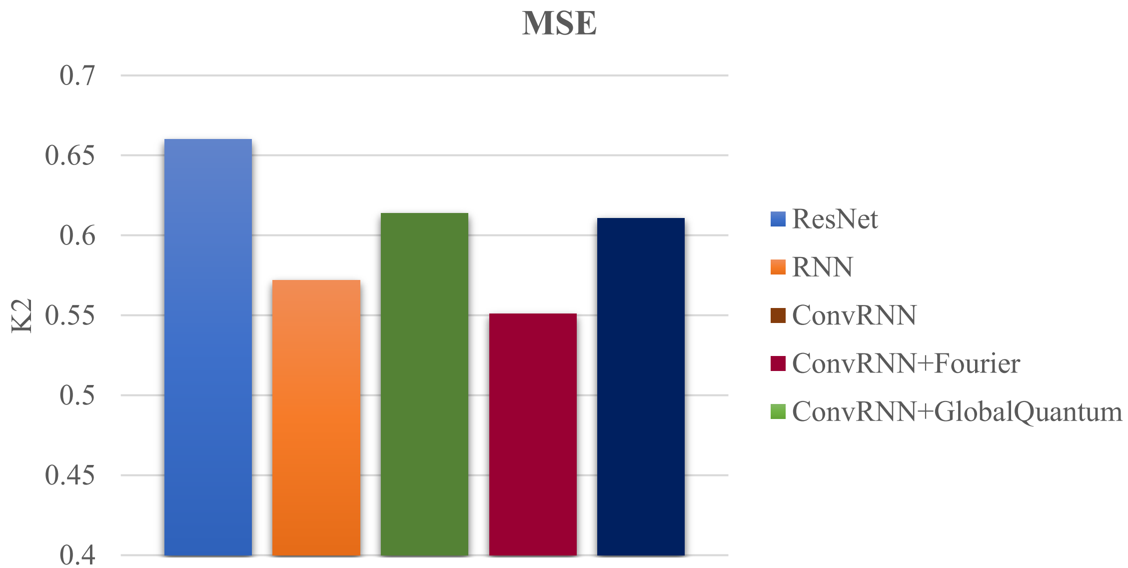


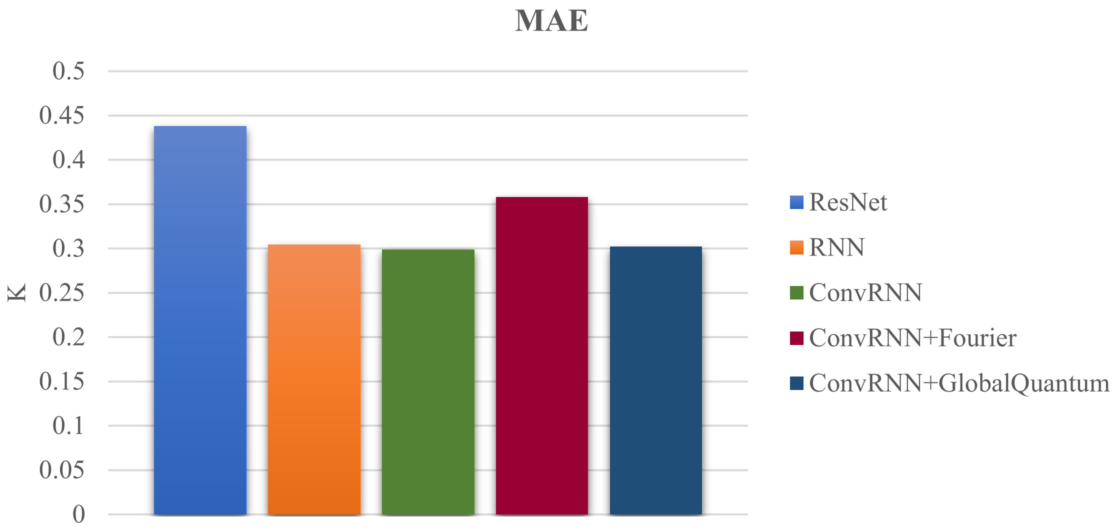
SAMPLER QNN
2-qubit circuit

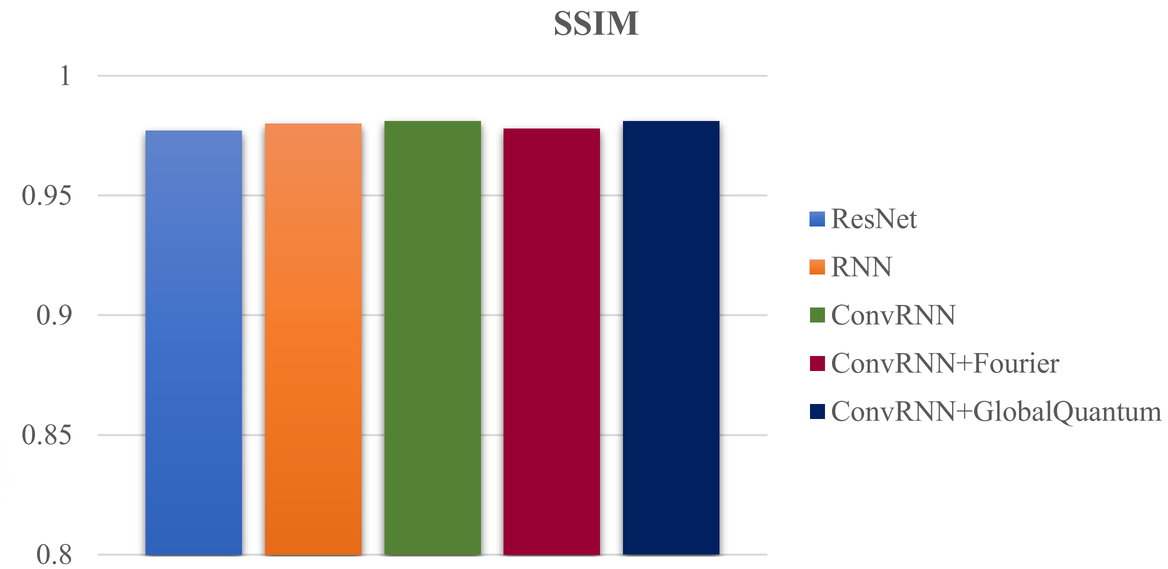
Amato et al., 2026 (in prep.)

AI models with advanced technologies: performance analysis

Mean Squared Error (MSE), Mean Absolute Error (MAE), Structural Similarity Index Measure (SSIM)







$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad \mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

MSE and MAE are "error" measurements, so they have to be close to 0, SSIM is a similarity index, so it has to be close to 1

Amato et al., 2026 (in prep.)

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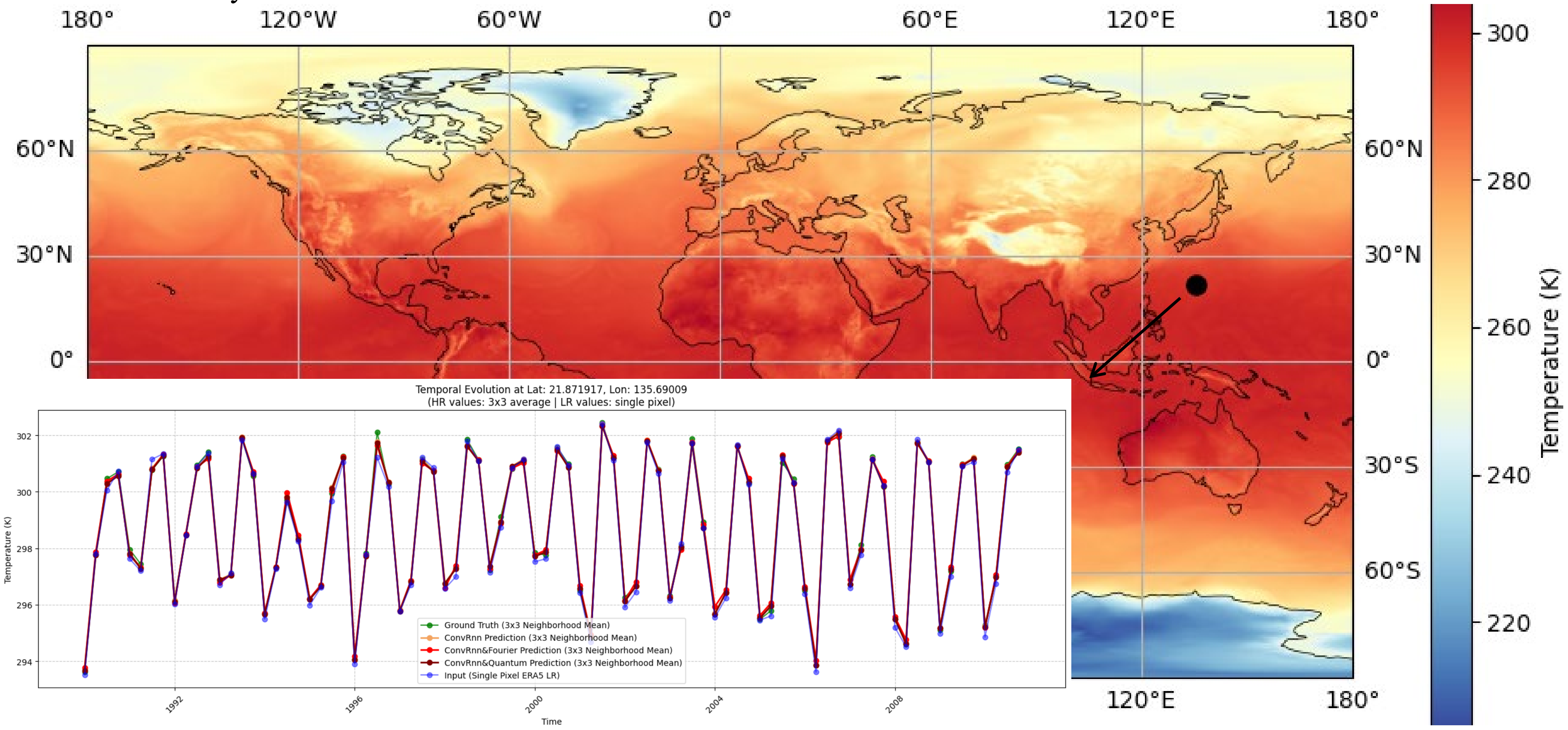
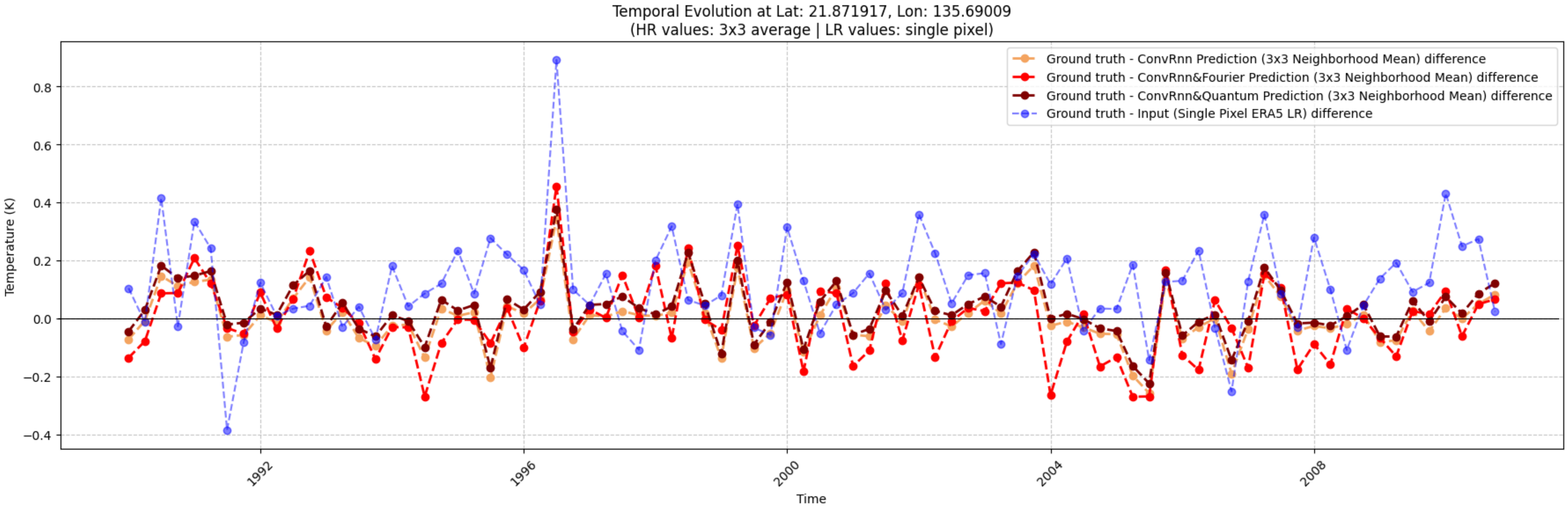
AI models with advanced technologies: super-resolution time series, difference ground truth – pred and ground truth - input

Considering a point close to Pinatubo, we can study the temporal evolution of temperature, comparing ground truth, prediction and input. A 3x3 buffer around the point is selected for ground truth and prediction, to reduce pixel variability and compare similar area and the models already trained are **tested** over 1990-2010 time window .



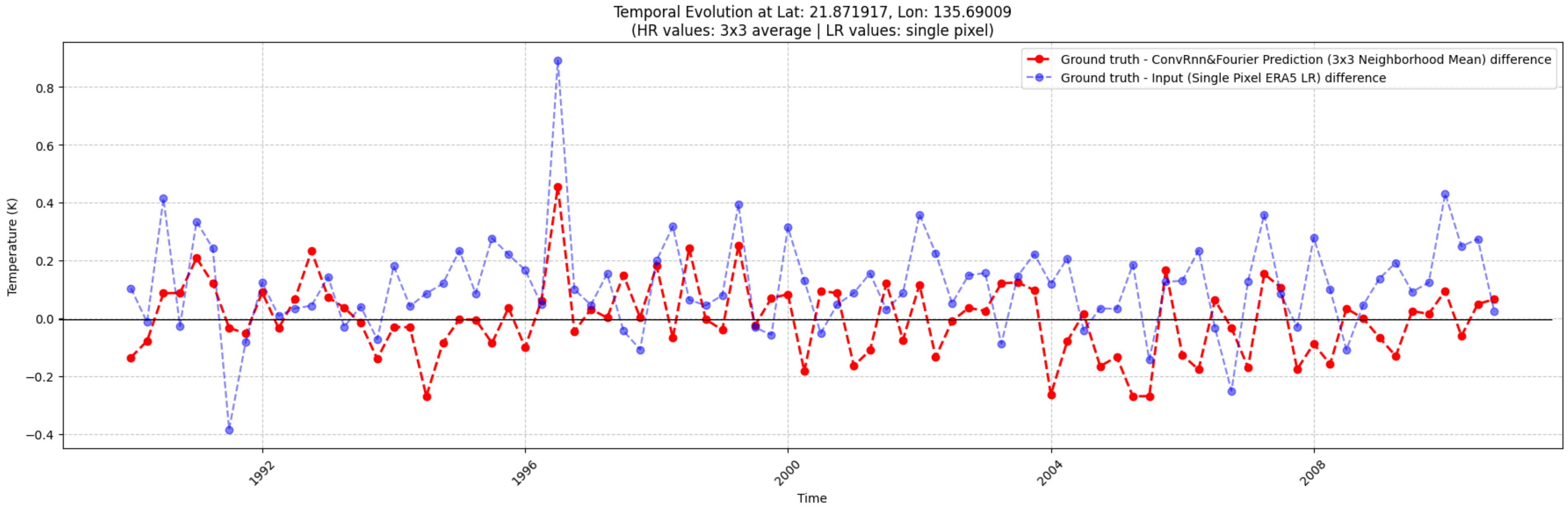
AI models with advanced technologies: super-resolution Pinatubo time series, difference ground truth – pred and ground truth - input

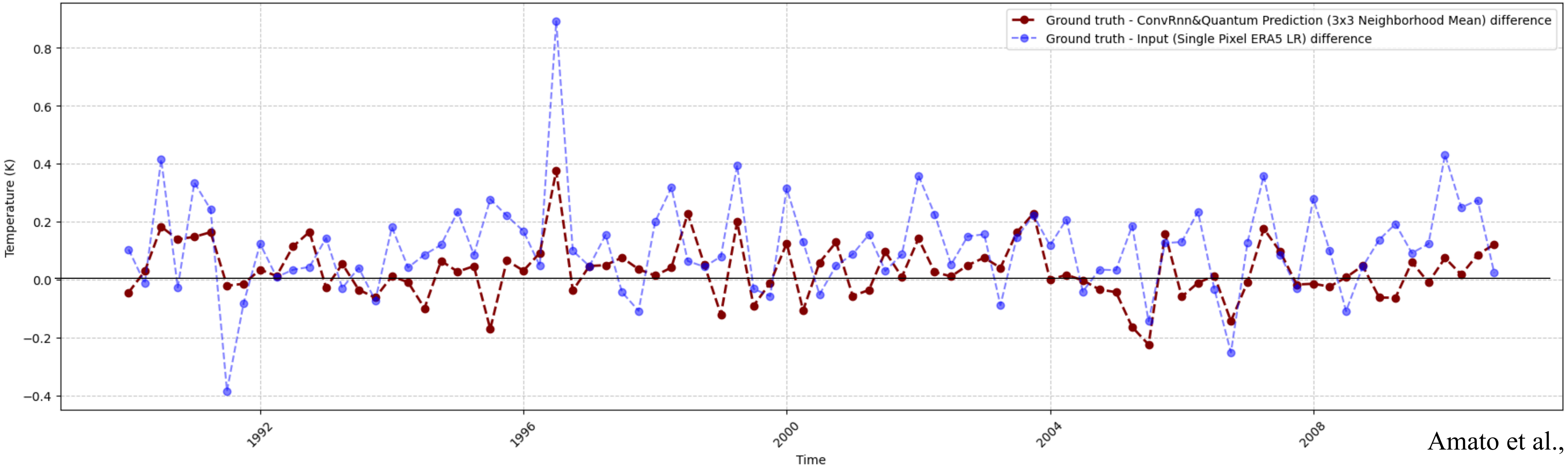


Comparison difference between ground truth and input and ground truth and prediction with ConvRnn, ConvRnn&Fourier, and ConvRnn&Quantum prediction, with 3x3 buffer.

Amato et al., 2026 (in prep.)

AI models with advanced technologies: super-resolution Pinatubo time series, difference ground truth – pred and ground truth - input





Residual analysis: both Fourier and Quantum model make errors close to zero line, performing effective **downscaling**, drastically reducing the thermal uncertainty of the input.

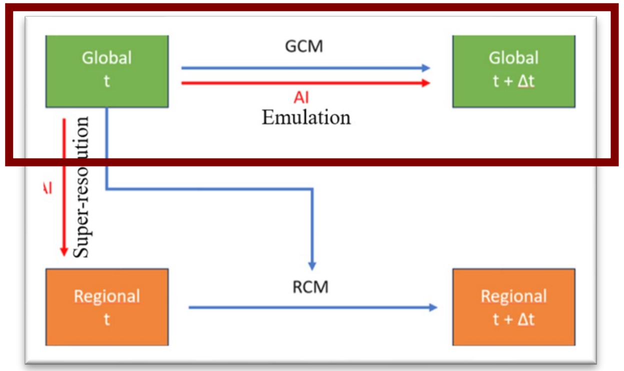
Fourier: remove high frequency noise but may underestimate;

Quantum: better mapping of complex forcings and rapid responses (expressivity), Quantum Bridge acts as a precision dynamic corrector

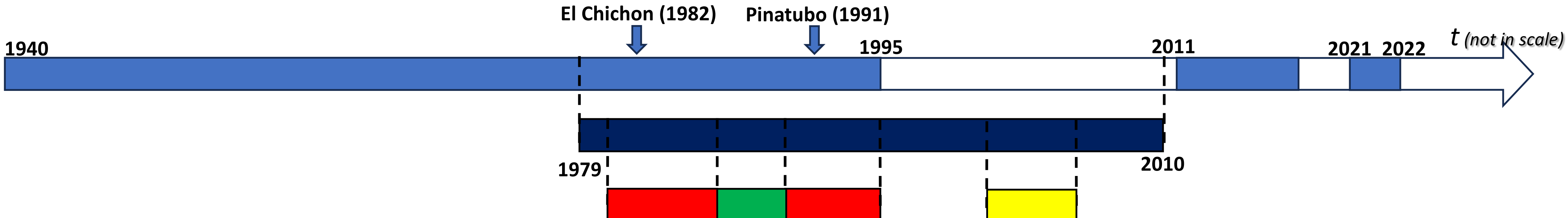
Amato et al., 2026 (in prep.)

2) AI-based emulators for climatic models: experimental protocol

- **Objective.** Assess whether ACE2-ERA5 trained model exhibits sensitivity to large volcanic forcing by comparing hindcasts spanning the **El Chichón and Pinatubo eruptions** (respectively April 1982 and June 1991), **the largest in ERA5 dataset,** with non-eruption periods.
- Two inferences during the same period (**1979-2010**) with different radiative forcings:
  - **Original Radiative Forcing:** Downward Shortwave Radiative Flux at Top of Atmosphere (**DSWRFtoa**)
  - **Adjusted Radiative Forcing:** DSWRFtoa + **Volcanic Effective Radiative Forcing (ERF)**
- Four hindcast windows, including both **training** and **test** periods:
  - **- 1981-1987**: in-training, includes the **El Chichón** period;
  - **- 1987-1990**: in-training, no major volcanic eruption.
  - **- 1990-1995**: in-training, includes the **Pinatubo** period;
  - **- 2001-2004**: test, no major volcanic eruption;



- **Why in-training years.** This isolates the question "does the model represent the forced signal?" before attributing errors to out-of-distribution generalization.
- **Test window role.** Provides a baseline to assess model stability and typical error magnitude outside the training distribution.



Watt-Meyer, Oliver, et al., *arXiv preprint arXiv:2310.02074* (2023)

ACE2-ERA5 train periods

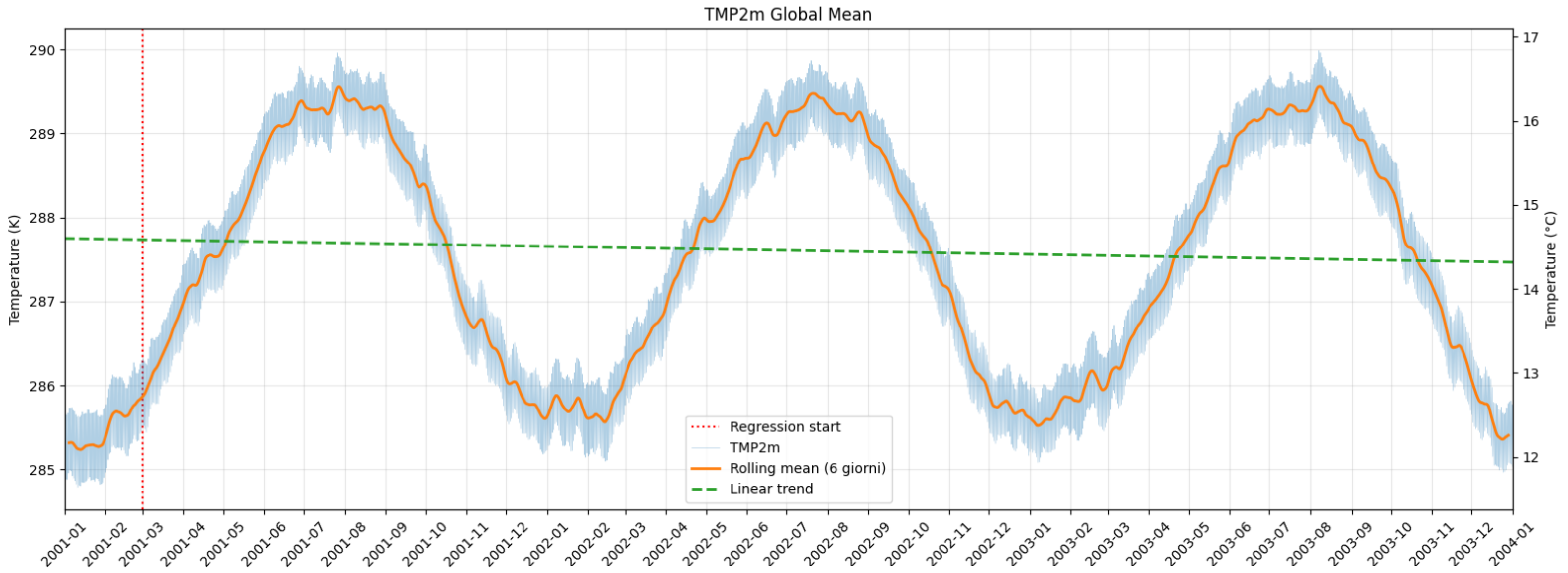
Inference windows with original radiative forcings and volcanic ERF forcings

Train window with volcanic activity

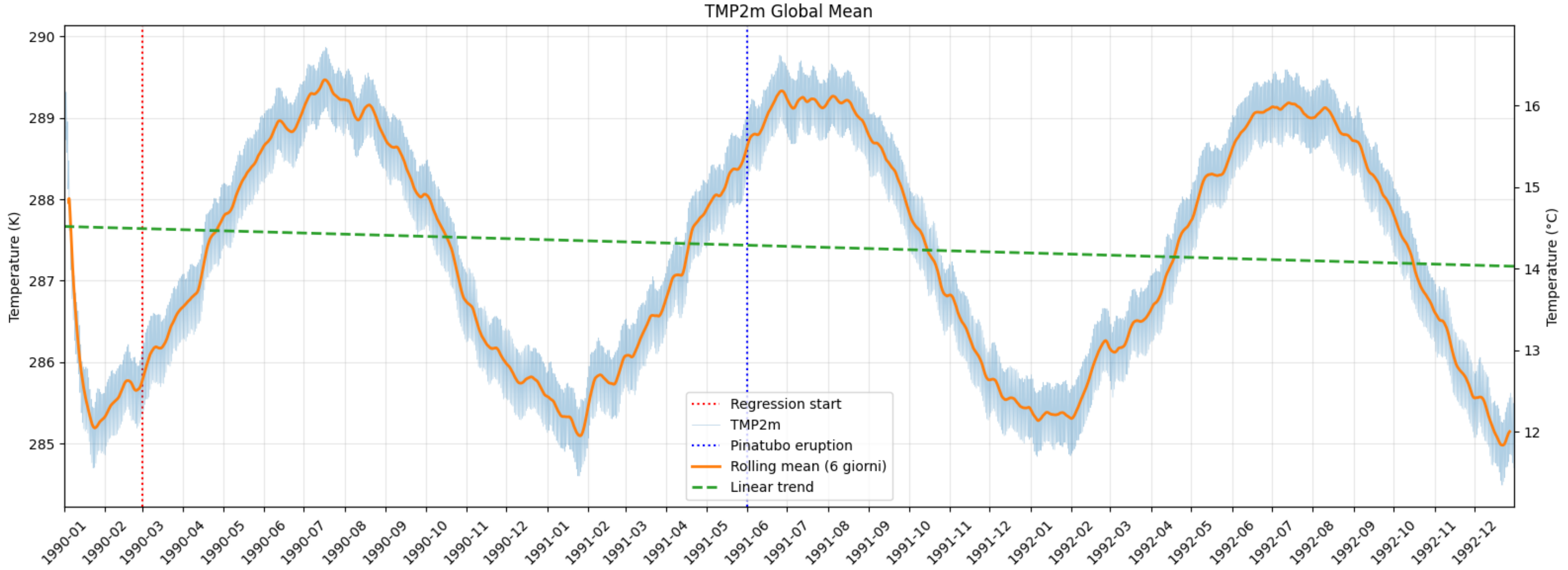
Train window without volcanic activity

Test window without volcanic activity

AI-based emulator: ACE inference



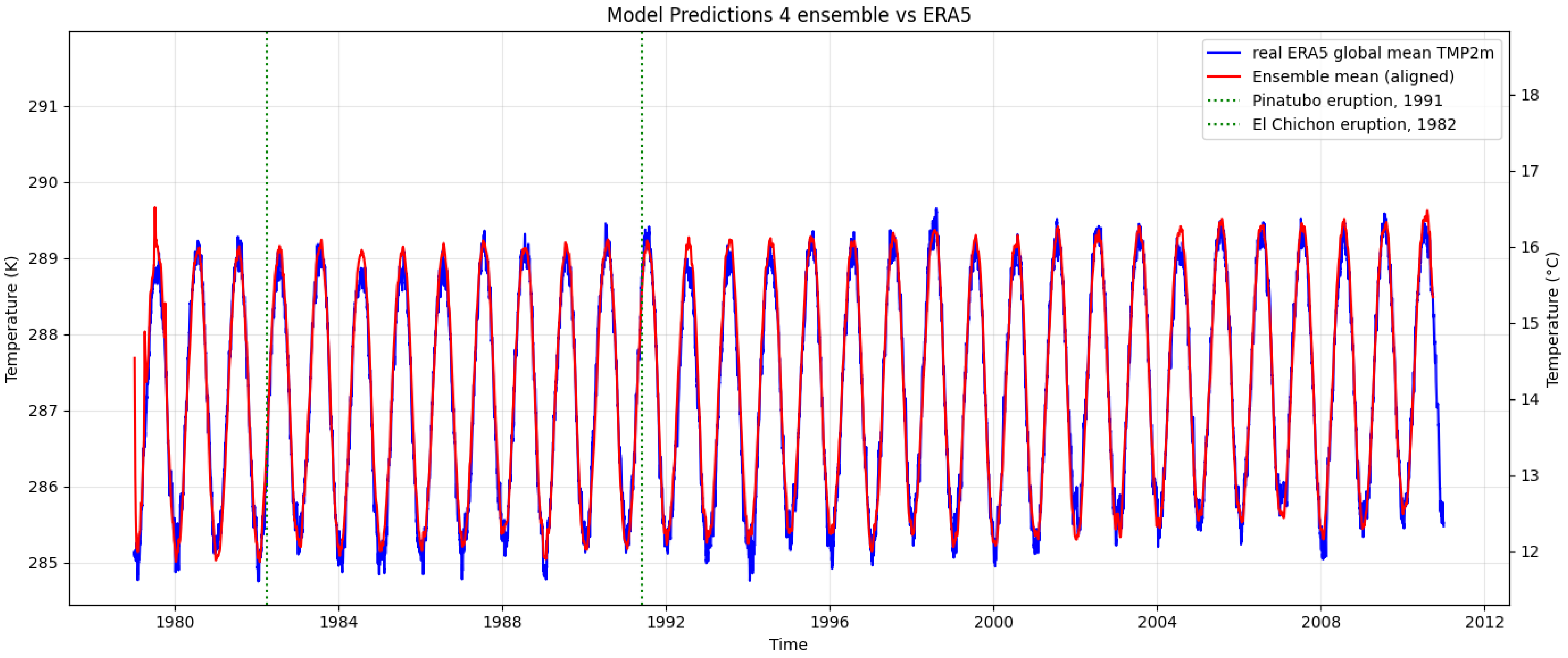
Single-member inference
2001-04 (Test window)



Single-member inference
1990-93 (Train window)

AI-based emulator: ACE inference – ERA5 comparison

Ensemble mean vs ERA5 **1979-2010**



Basile et al., 2026 (in prep.)

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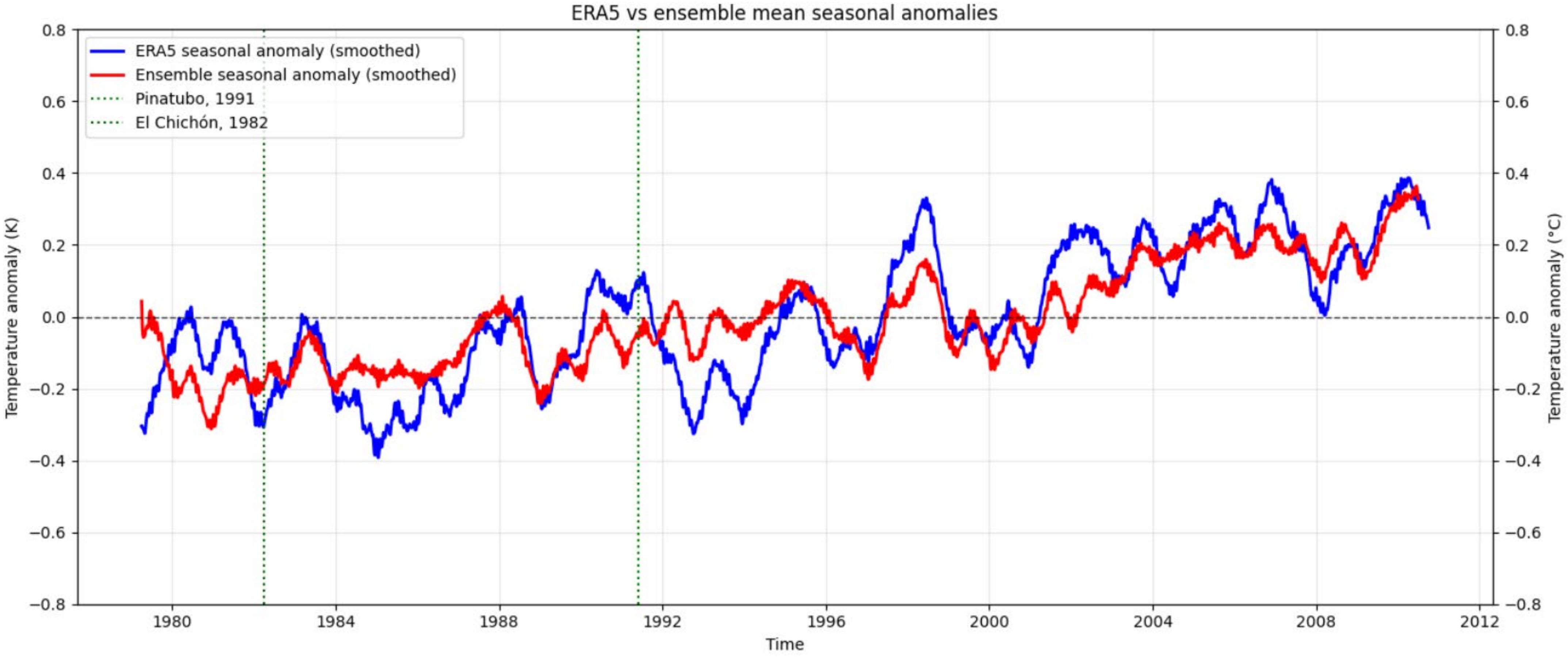
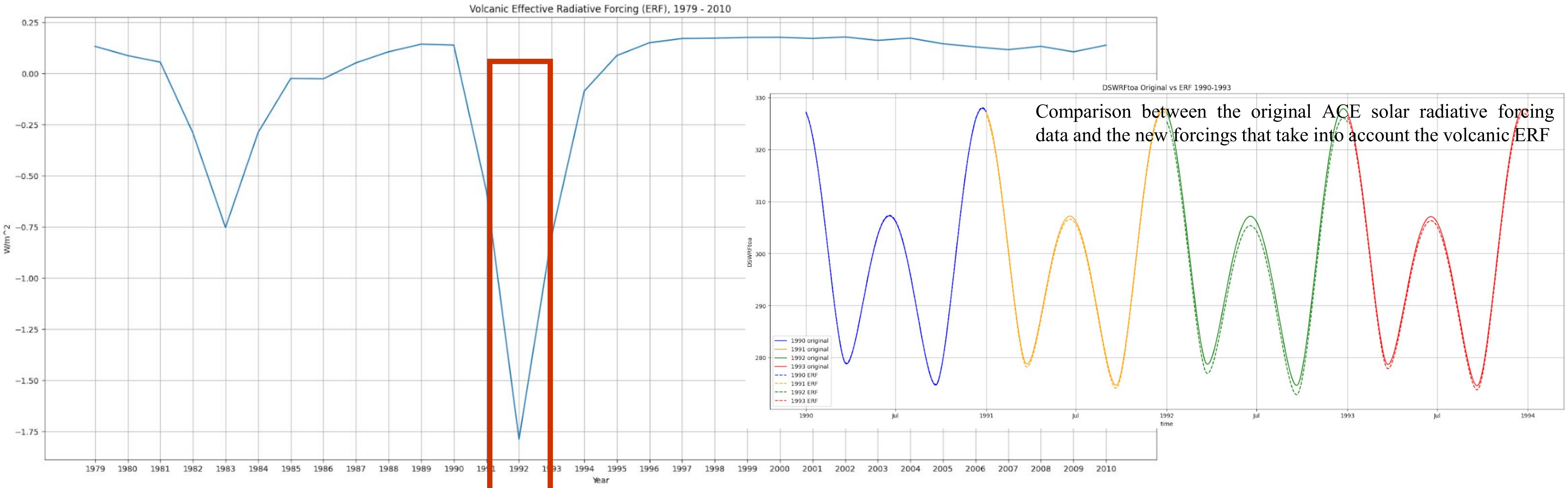
AI-based emulator: ACE inference - ensemble



Seasonal effects were eliminated by calculating the average of each month and subtracting it from the original series (separately for ERA5 and predictions), then applying the 6-month moving average. Removing seasonality should leave internal variability and climate trend intact. The values fluctuate around zero, but the **trend is increasing over the years**. Regarding internal variability and focusing on post-eruption data, **ERA5 shows a negative response** (more clearly after Pinatubo in 1991), while in **predictions they are little or nonexistent**: the model, at least globally, does not account for the climate variability due to an eruption, even a large one.

Basile et al., 2026 (in prep.)

AI-based emulator: volcanic forcing



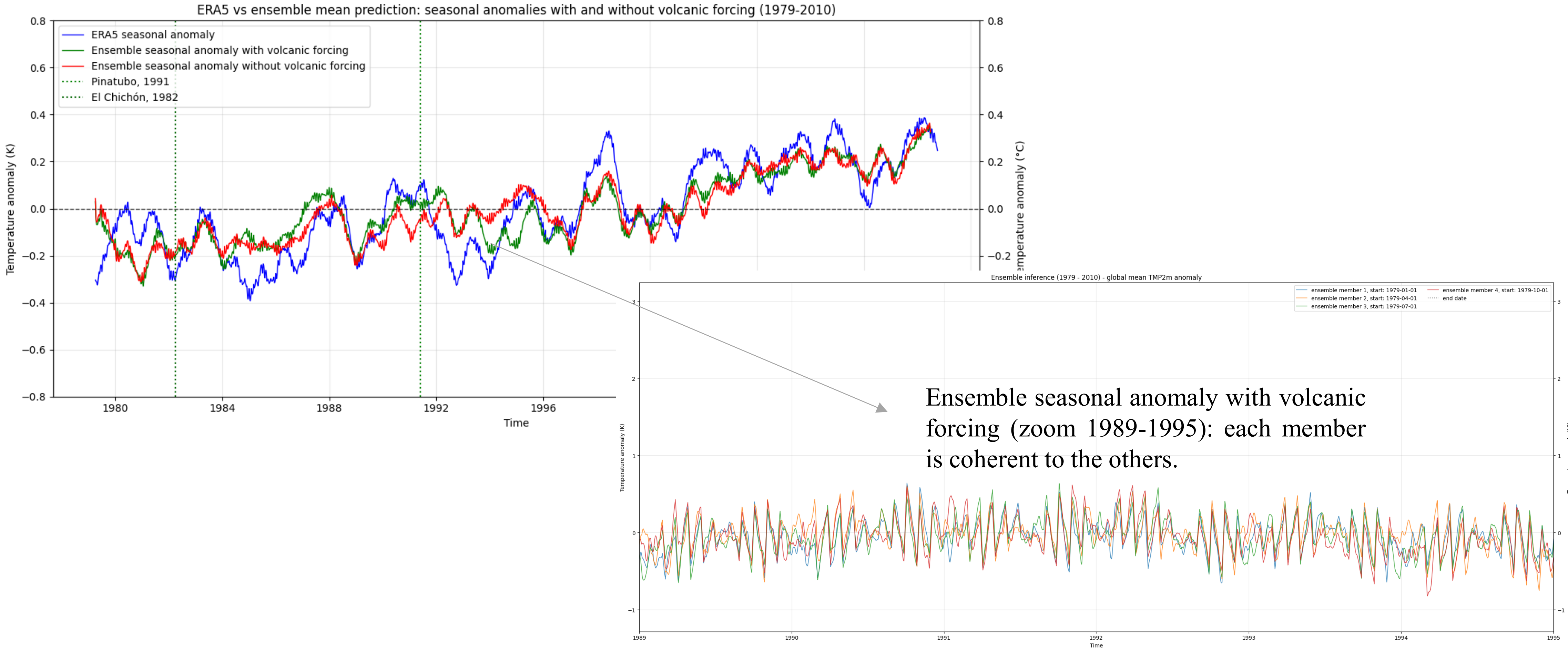
Pinatubo eruption

Comparison between the original ACE solar radiative forcing data and the new forcings that take into account the volcanic ERF

<u>DSWRFtoa</u>	<u>DSWRFtoa + Volcanic ERF</u>
1990: Max: 327.89 Min: 274.71	1990: Max: 328.03 Min: 274.85
1991: Max: 327.86 Min: 274.69	1991: Max: 327.29 Min: 274.11
1992: Max: 327.83 Min: 274.66	1992: **Max: 326.04 Min: 272.87**
1993: Max: 327.76 Min: 274.60	1993: **Max: 326.97 Min: 273.81**

Volcanic forcings within the Effective Radiative Forcing (ERF) of the IPCC Sixth Assessment Report (AR6) represent the natural influence on Earth's radiation caused by volcanic eruptions, in particular they are changes in the Earth's energy balance caused by the release of **aerosols** (primarily sulfur dioxide, SO_2) into the stratosphere following explosive volcanic eruptions → to be added to ACE's original TOA solar radiative forcing

AI-based emulator: ACE inference – ensemble with volcanic forcing



Seasonal effects eliminated at the same way, then applying the **6-month moving average,** to leave internal variability and climate trend intact, with and without volcanic forcing (each ensemble **coherent** to each other).

The values fluctuate around zero, and the two **trends are increasing over the years**. Regarding internal variability and focusing on post-eruption data, **ERA5 shows a negative response** (more clearly after Pinatubo in 1991), **little differences** are present in other trends.

Basile et al., 2026 (in prep.)

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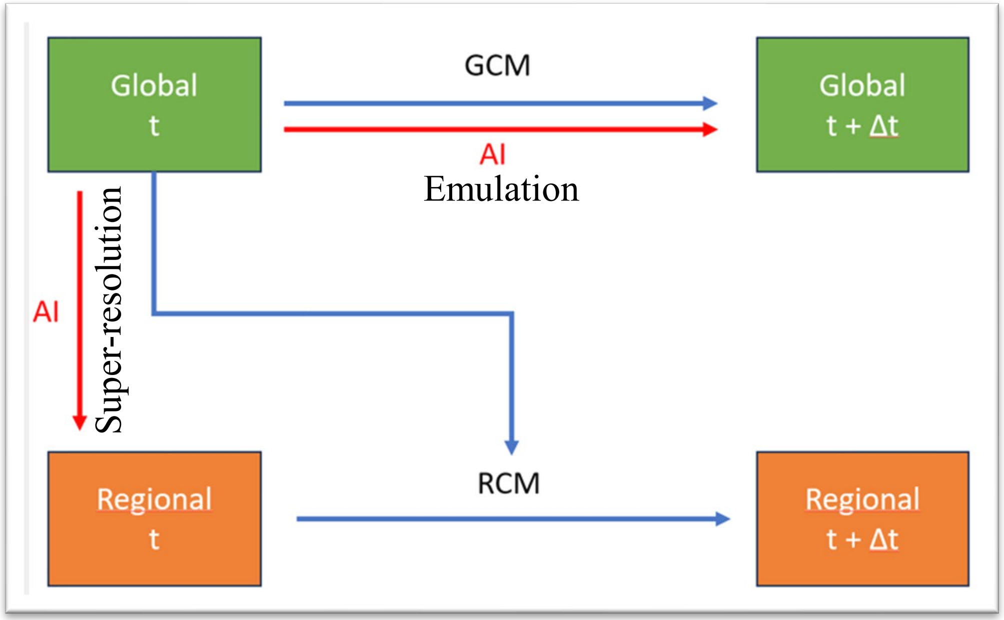
Take-home messages

- **Super-resolution models** effectively reconstruct fine-scale thermal structures that maintain consistency with high-resolution ground truth; **Fourier** module acts as a spectral refiner that ensures the coherence of the reconstructed thermal field, **Quantum Bridge** provides the model with the expressiveness needed to correct for more pronounced local biases.

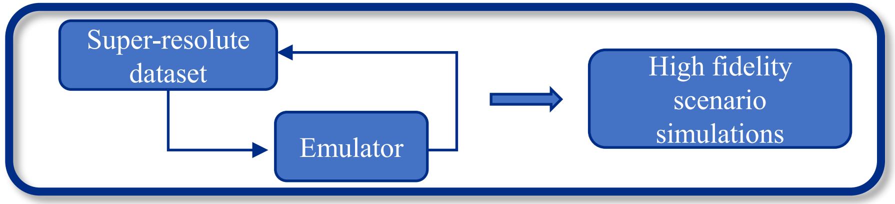
- **ACE-ERA5 comparison** helps us to determine the model's capacity to accurately respond to abrupt stratospheric aerosol injections and their subsequent impact on global and regional thermal structures; the introduction of volcanic forcings increase the ability to catch impacts.

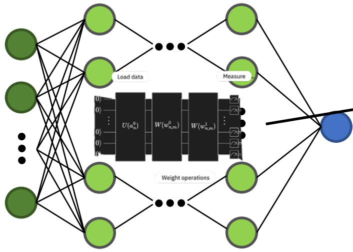
General framework



Next steps

- Expand application analysis to other datasets
- Combined pipeline
- Use of more data and enhanced models to improve performance
- Improve Quantum AI, to enhance functionalities
- Combine Quantum and Fourier layers in a unique model





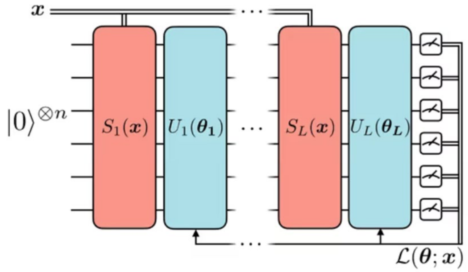


Fig source: Quantum Machine Learning course
IBM Quantum Platform

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... thanks!