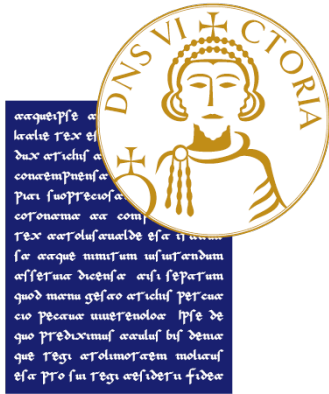


Quantum Advances in Earth Observation: Unlocking the Potential of Quantum Machine Learning Algorithms

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Summary

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- ❖ Hybrid QNN for EO Classification
- ❖ Quantum Image Processing/Filtering
- ❖ Hybrid Quantum Model for enhanced EO prediction:
- ❖ Quantum Hyperparameters selection
- ❖ Conclusions
- ❖ References

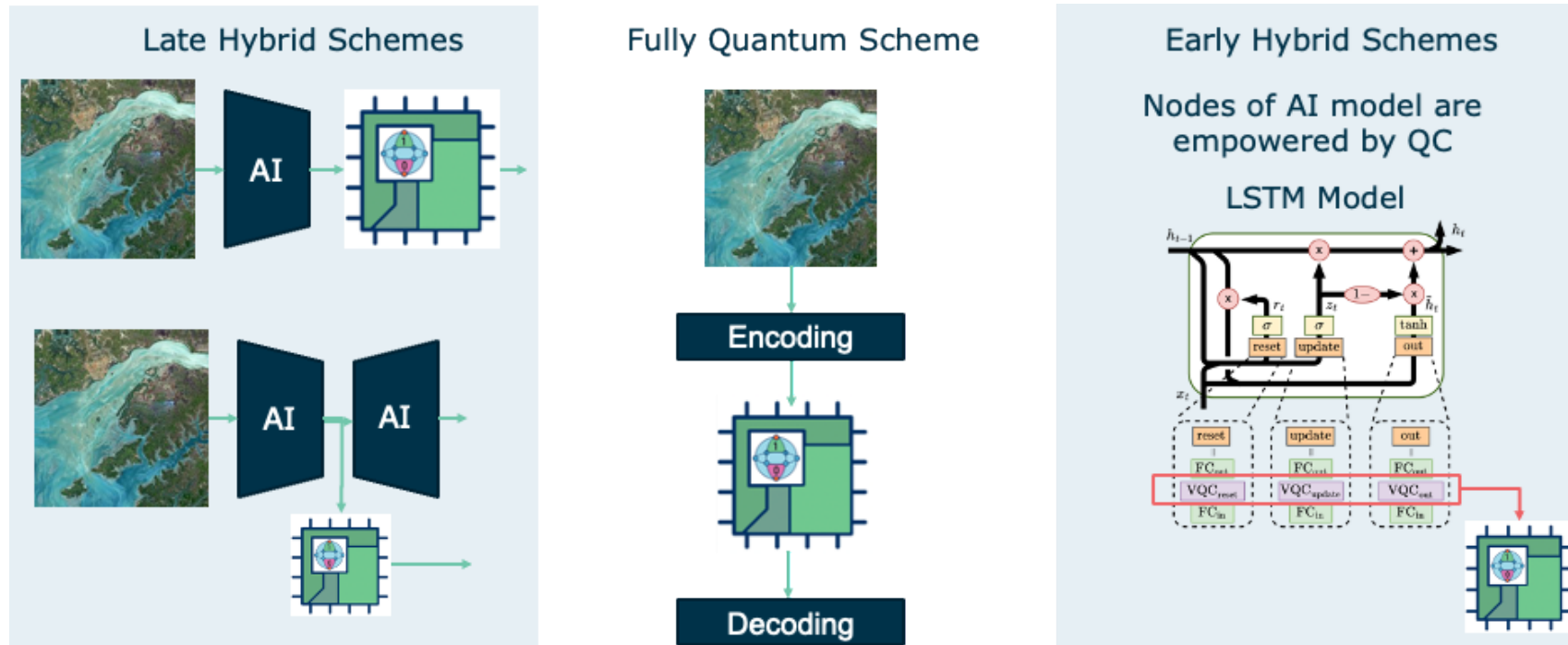
Motivation

- ❖ Earth Observation (EO) at full speed.
In space: New satellites with various sensors.
On ground: Big Data: over 150 terabytes per day.
- ❖ A completely new challenge is arising: the limit of classical computing soon to be reached!
- ❖ Quantum computing has the potential to improve performance, decrease computational costs and solve previously intractable problems in EO.
- ❖ Our research focuses on investigating and evaluating suitable QML approaches that can address current EO challenges.



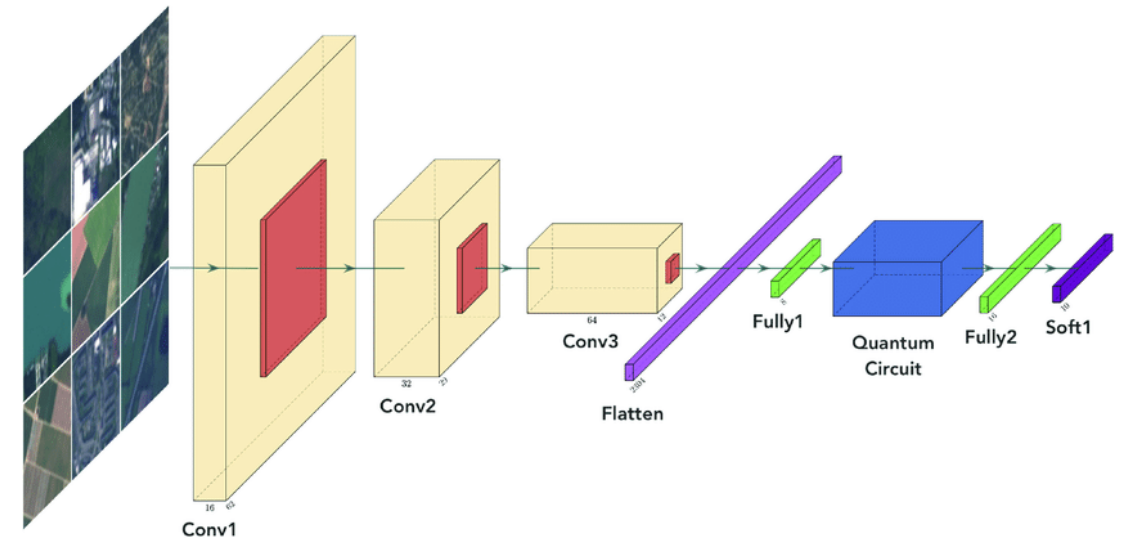
Quantum Machine Learning for EO

Quantum machine learning is a research area that explores the interplay of ideas from quantum computing and machine learning. We adopted this vision and applied it to EO.



Hybrid QNN for Eo Classification

- ❖ In [1] we proposed a proof-of-concept for a hybrid QNN applied EO land-use land-cover binary classification (few qubits and one circuit layer).
- ❖ In [2], we improved our first solution to perform multiclass classification, proving that the real amplitudes circuit, exploiting **quantum entanglement**, achieves the best classification scores. Starting from these results, we explored solution with more layers and more qubits, but also different kinds of layers such as quantum convolution operations.

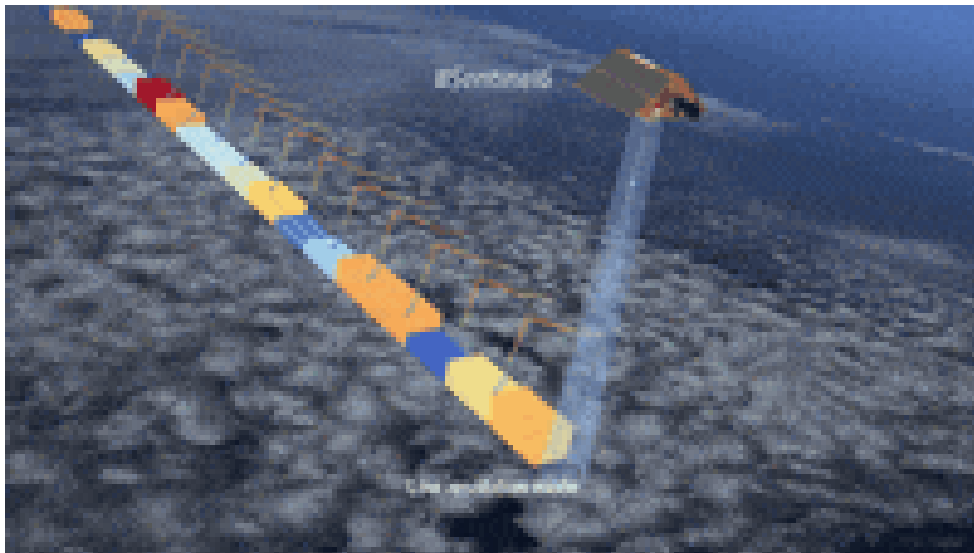


On circuit-based Quantum Hybrid neural network [2]

Observing Earth through SAR

Advancements in Earth Monitoring

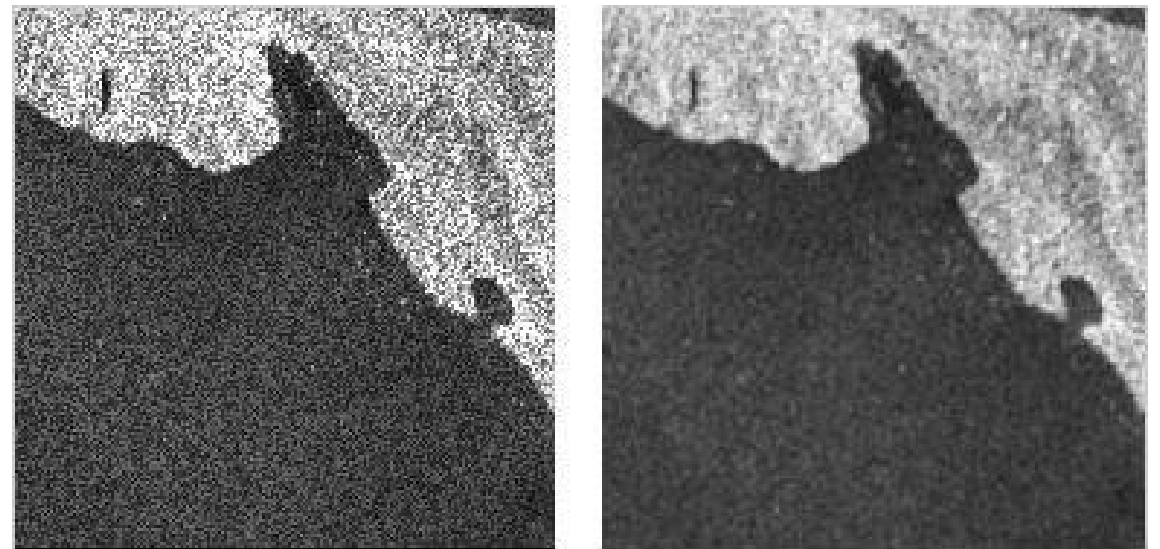
SAR technology has revolutionized our ability to monitor the planet, providing detailed analysis of terrestrial surfaces regardless of weather conditions.



Sentinel-1 (ESA)

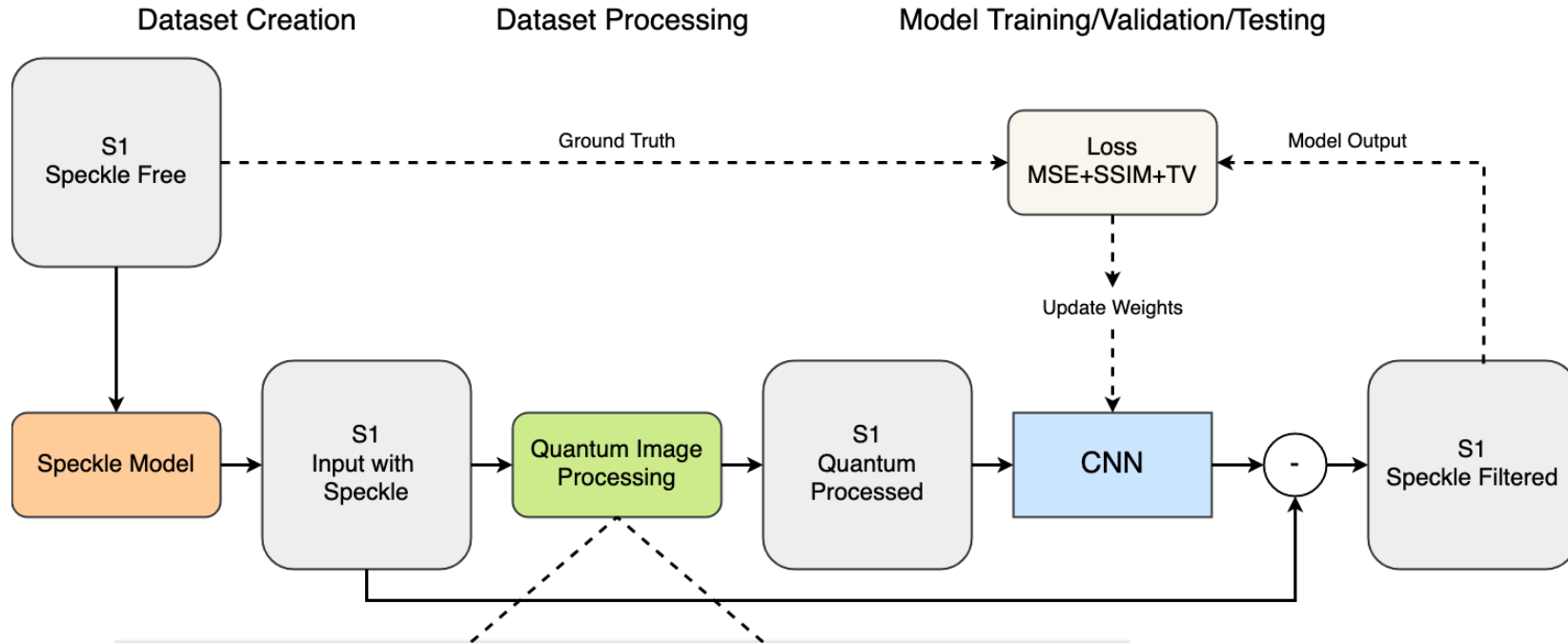
Challenge with Speckle

The acquisition of SAR images is often compromised by speckle, a granular disturbance that affects the quality of results and poses a significant challenge in Earth Observation.



Speckle Removal in grayscale SAR image [3]

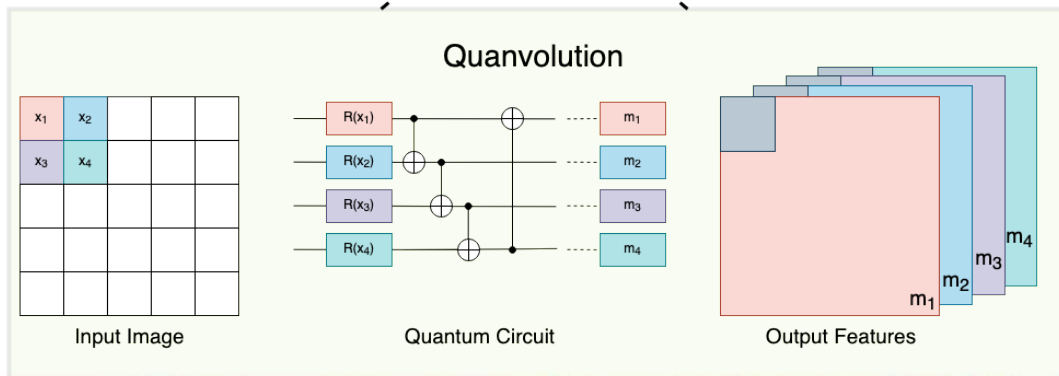
Method



❖ To address this challenge, in [4] we introduce the **QSpeckleFilter**.

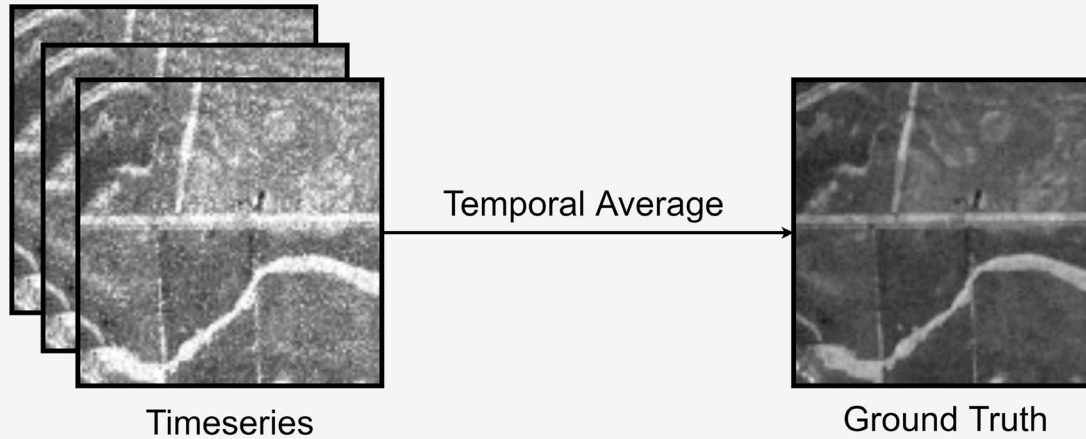
❖ **Quanvolutional operator:** Pre-processing the dataset using the Quanvolutional operator to expand the original domain of the features map.

❖ **Removing Speckle noise:** speckle is subtracted from SAR images through a subtractive layer.

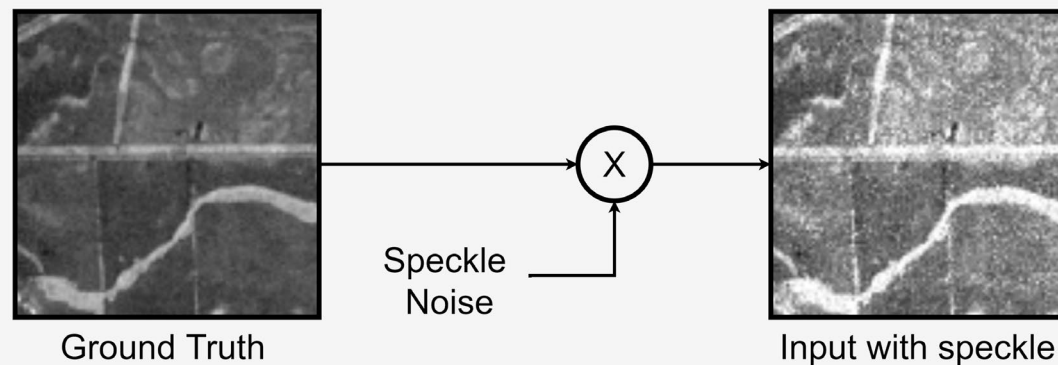


Dataset creation

Step 1 - Download of timeseries from GEE and apply temporal average



Step 2 - Generate speckle noise to be applied to the ground truth

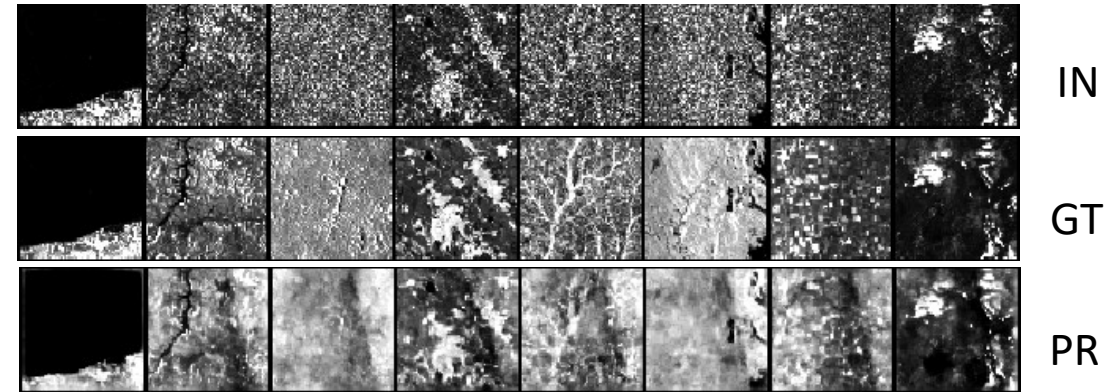


Description of the necessary steps for the creation of the suitable dataset, presented by Sebastianelli et al. [5].

Results

Favorable Outcome

Displaying a smoothing effect on the filtered images and showcasing a transformative enhancement in performance metrics such as PSNR and SSIM.



Comparison with Previous Work

Demonstrating the potential of Quanvolution in image processing and surpassing the metrics of previous methods.

Model	PSNR	SSIM
Ground Truth	$+\infty$	1.0
Speckled	15.70	0.58
Sebastianelli et al.	19.21	0.75
QSpeckleFilter	21.72	0.81

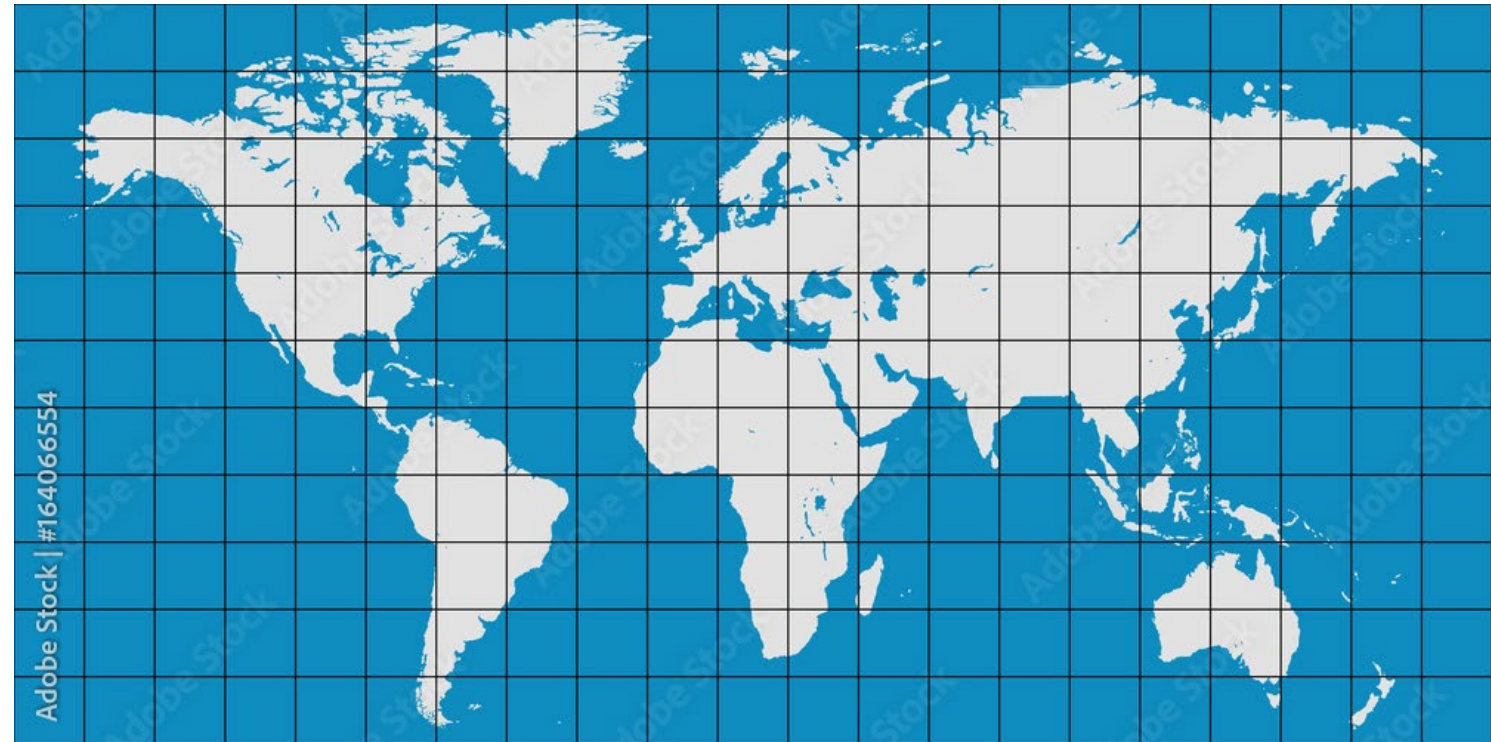
Limitations of QCNNS

Limitations of Quantum Convolutional Neural Networks (QCNNS):

Challenges in capturing global-scale dependencies or events, such as El Niño fluctuations.

CNNs' Limitations: shift-equivariance, spatial proximity bias, inflexibility.

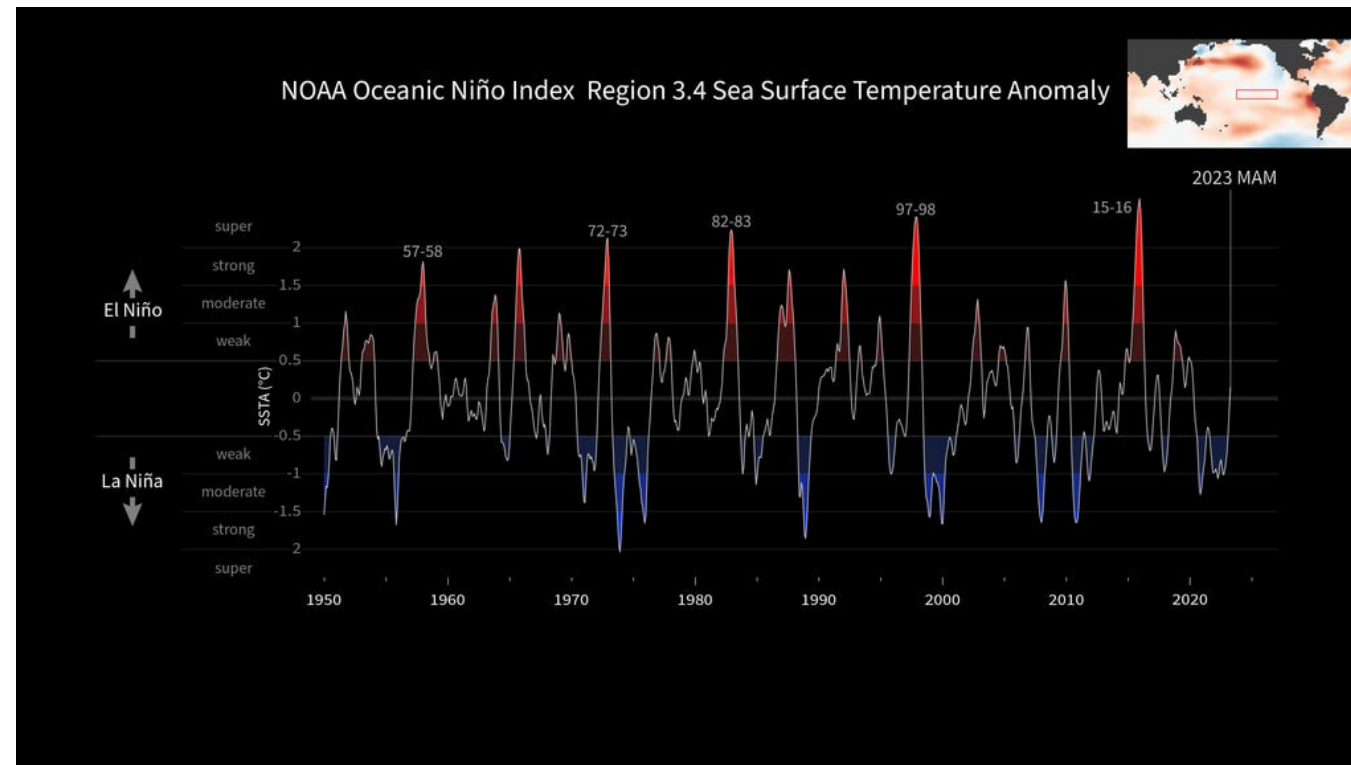
Objective: Extend the exploration of Hybrid Quantum Graph Convolutional Neural Networks (HQGCNNs) for predicting complex phenomena such as the Oceanic Niño Index (ONI), as described in [6].



Understanding El Niño phenomenon

Characteristics: Abnormal warming of the central and eastern tropical Pacific Ocean.

The Oceanic Niño Index (ONI) is NOAA's primary indicator for monitoring the ocean part of the seasonal climate pattern called the El Niño-Southern Oscillation, or “ENSO”



Dataset

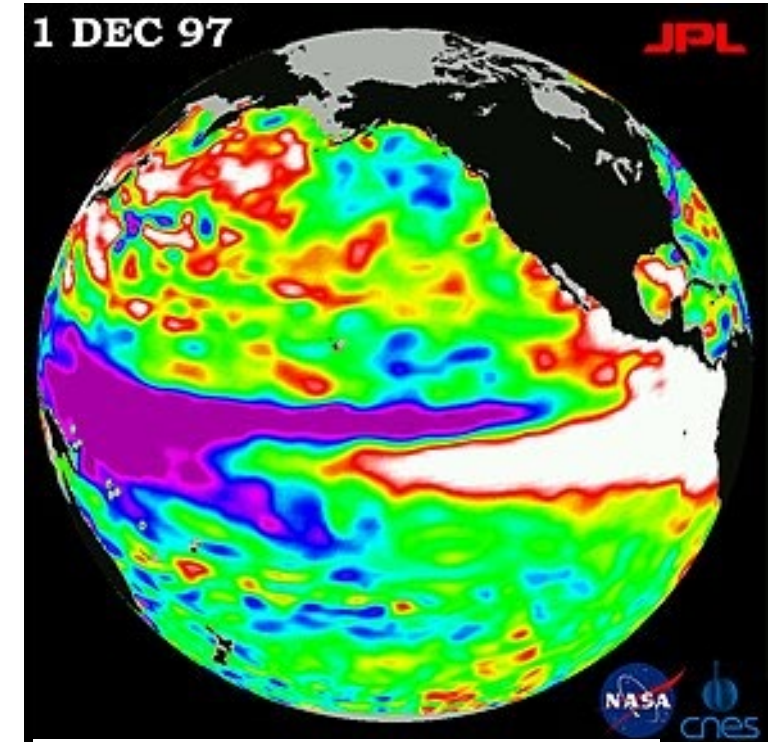
Train Set: SODA reanalysis dataset (1871-1973).

Test Set: GODAS dataset for the period of 1984 to 2017.

Augmentation: Inclusion of climate model simulations from Coupled Model Intercomparison Project Phase five (CMIP5).

Resolution and Geographical Range: Utilization of datasets in a resolution of 5 degrees and specific geographical locations.

Prediction Target: Oceanic Niño Index (ONI), primary index for tracking the ocean part of ENSO, and ENSO climate patterns.

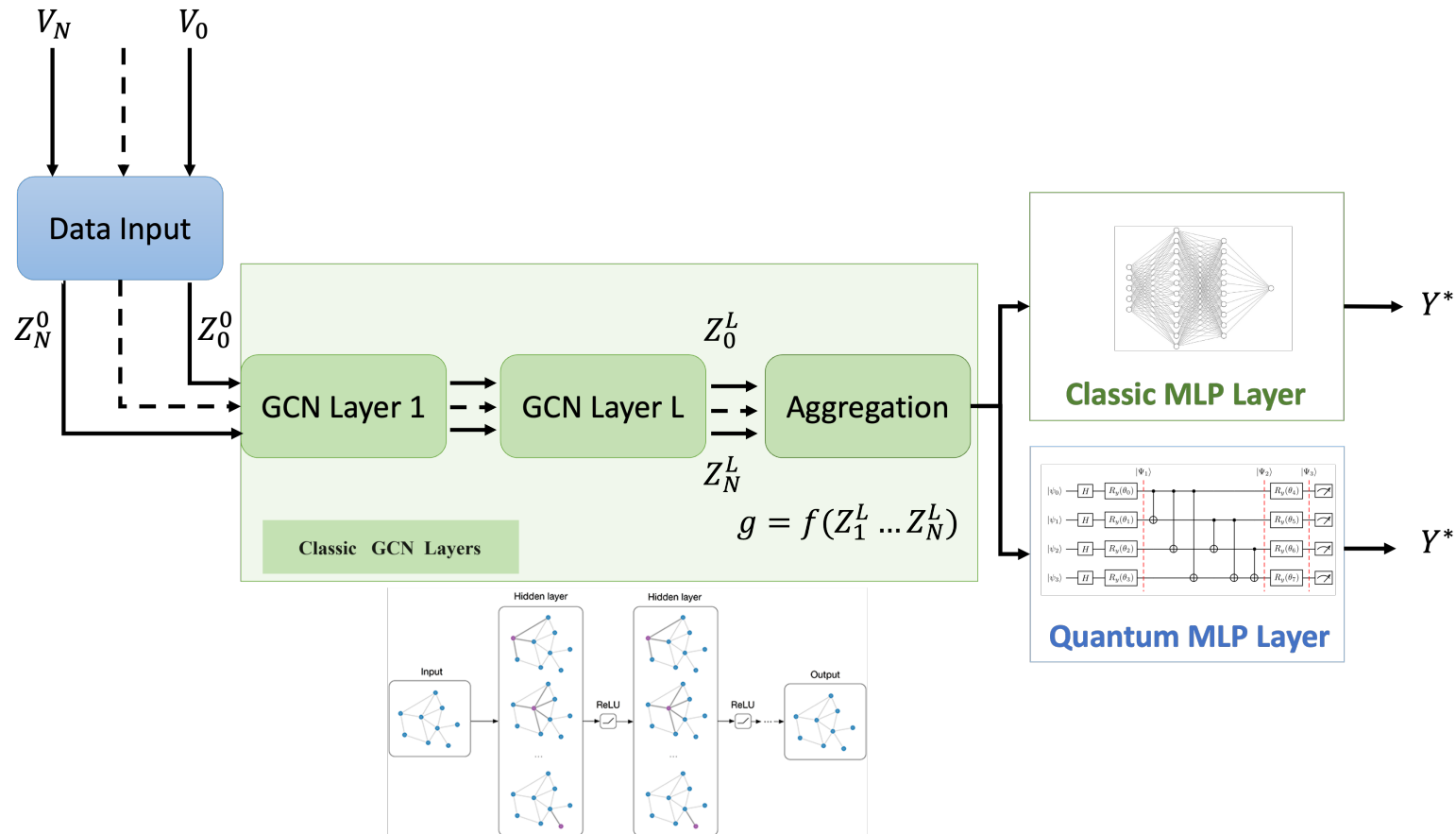


The 1997-98 El Niño observed by the TOPEX/Poseidon satellite showed warm water areas outside the western tropical coasts of the northern Southern Hemisphere and throughout Central America, along the eastern and southwestern Pacific Ocean (warm water in white)
https://www.jpl.nasa.gov/news/releases/97/elni_noup.html.

Method

GCNN: Capturing spatial features [7].
Quantum MLP: Exploiting quantum entanglement for enhanced performance.

Amplitude Encoding: Strategic choice for the large size of data. **Tested Circuits:** Basic and Strongly Entangled and Random Circuit.



Results

Optimal Configuration: Strongly Entangled Circuit with 8 layers and 10 qubits for $n=1$ and 9 layers and 9 qubits for $n=2$.

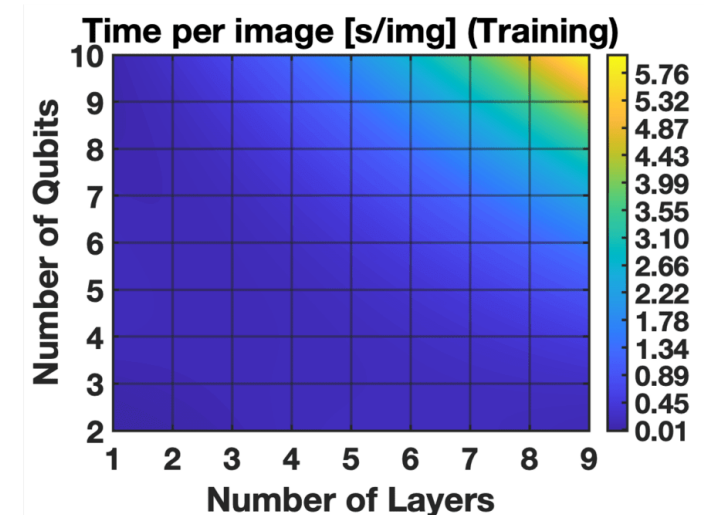
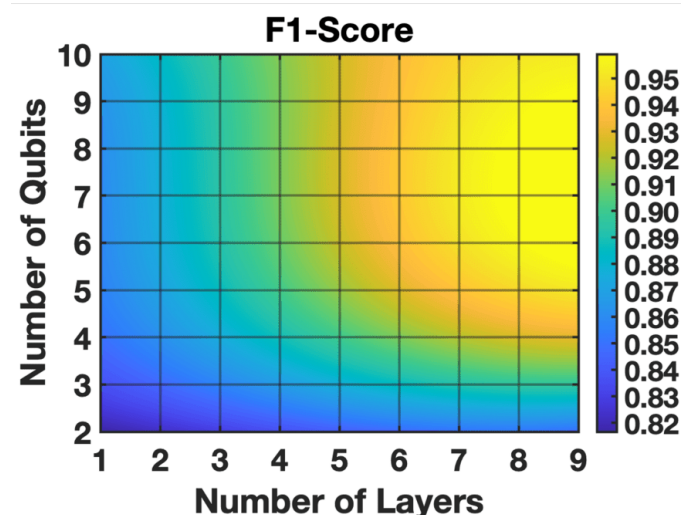
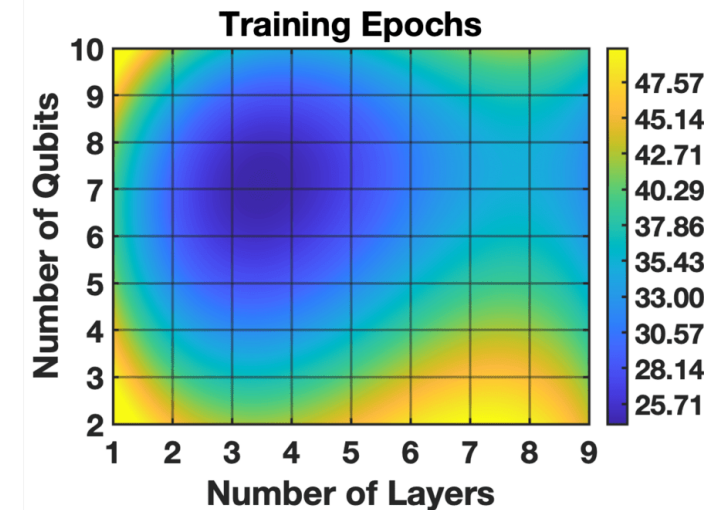
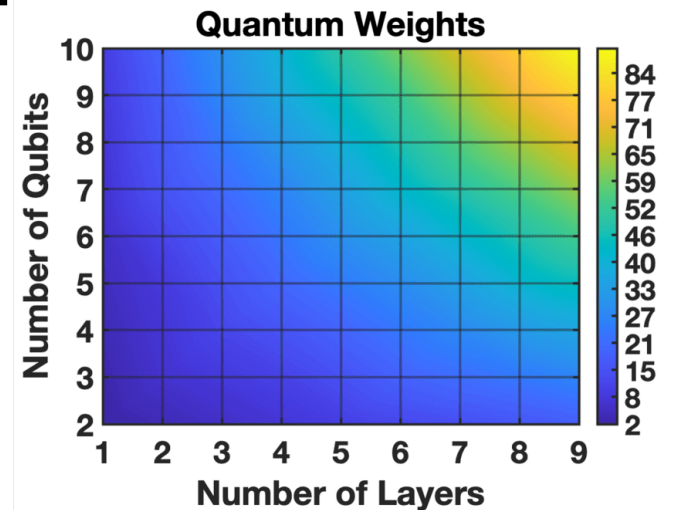
Performance: Surpassing state-of-the-art (SOTA) models with high efficiency and minimal training epochs. QGraphino achieves all-season correlation skill of 0.975 in one-month prediction and 0.937 in two-month prediction.

Model	$n = 1$	$n = 2$
Graphino	0.971	0.934
SINTEX-F	0.890	0.840
CNN	0.942	0.916
QGraphino	0.975	0.937

Quantum Hyperparameters Selection

In all these works, it is necessary to tune the quantum components to enhance performance.

In [8] we proposed guidelines on the hyperparameter tuning of the quantum part, working in the direction of demonstrating the quantum advantage for RS data processing and allowing us to show that there are more convenient solutions to simply increasing the number of qubits.



Conclusions

- ❖ This line of research has introduced a diverse portfolio of hybrid quantum algorithms, to tackle the most pressing challenges in geospatial data analysis.
- ❖ With this research we are contributing in the evaluation of potential of Quantum Computing for solving complex EO problems.
- ❖ It is evident that QML for EO in RS represents a truly cutting-edge and promising field with immense potential.
- ❖ There are currently only a limited number of research papers published in this area.
- ❖ This scarcity of publications underscores the untapped opportunities and the need for further exploration and research in harnessing the power of QML for advancing our understanding and applications in RS for EO.

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Thank you for your attention!

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