Quantum Computing for Earth Observation (QC4EO)

Advances and Challenges in Generative AI and Quantum Neural Networks

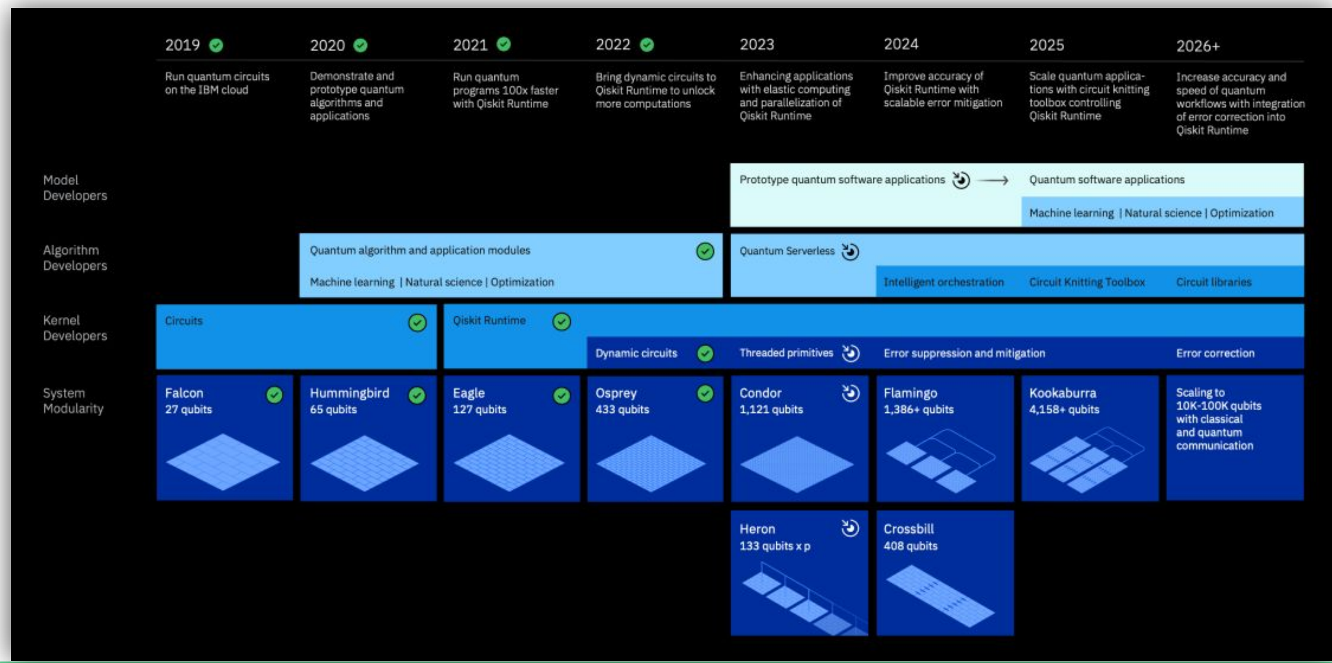
Bertrand Le Saux

HDCRS Summer School 2024/06/04

QC4EO: Motivations and Status

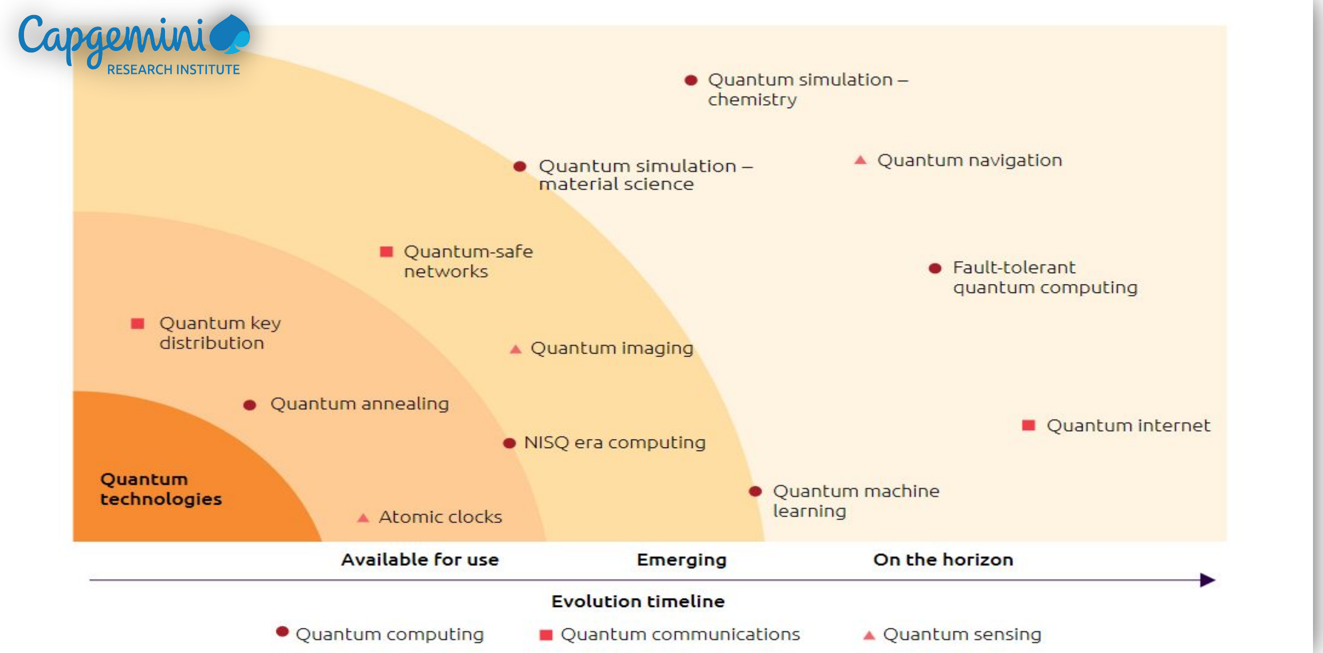
QC4EO: why now?

Large manufacturers have roadmaps showing progress from research to operations in the next decades, e.g. IBM roadmap



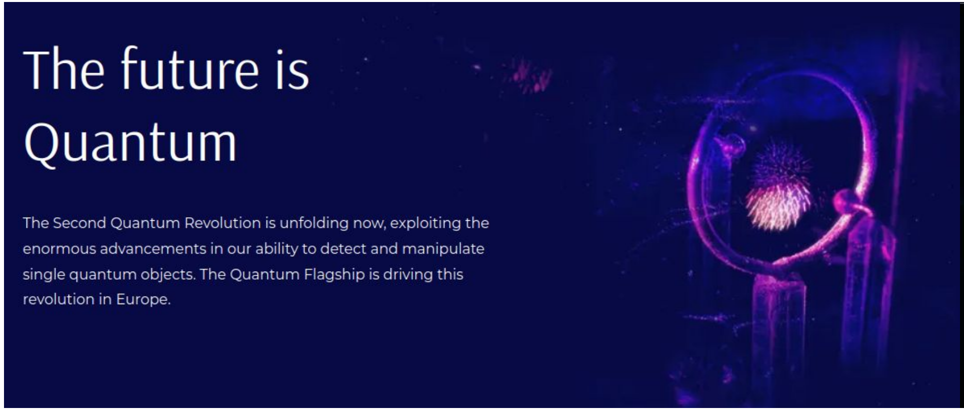
QC4EO: why now?

Large manufacturers have roadmaps showing progress from research to operations in the next decades, e.g. Cap Gemini roadmap



QC4EO: why now?

European Commission initiatives: QC Flagship x Destination Earth

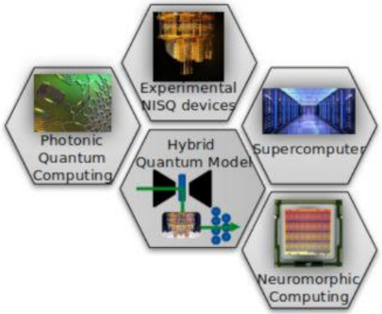


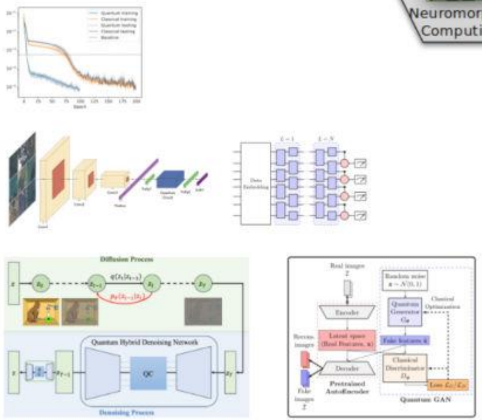
QUANTUM FLAGSHIP https://qt.eu/

https://destination-earth.eu/

QC4EO status

ESA's initiative to develop the Quantum Computing x Earth Observation ecosystem

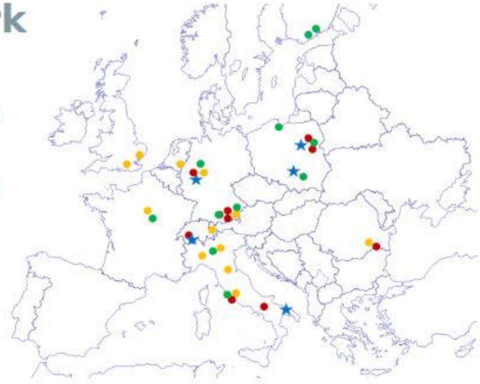




QML Research Sprints

QC4EO Network

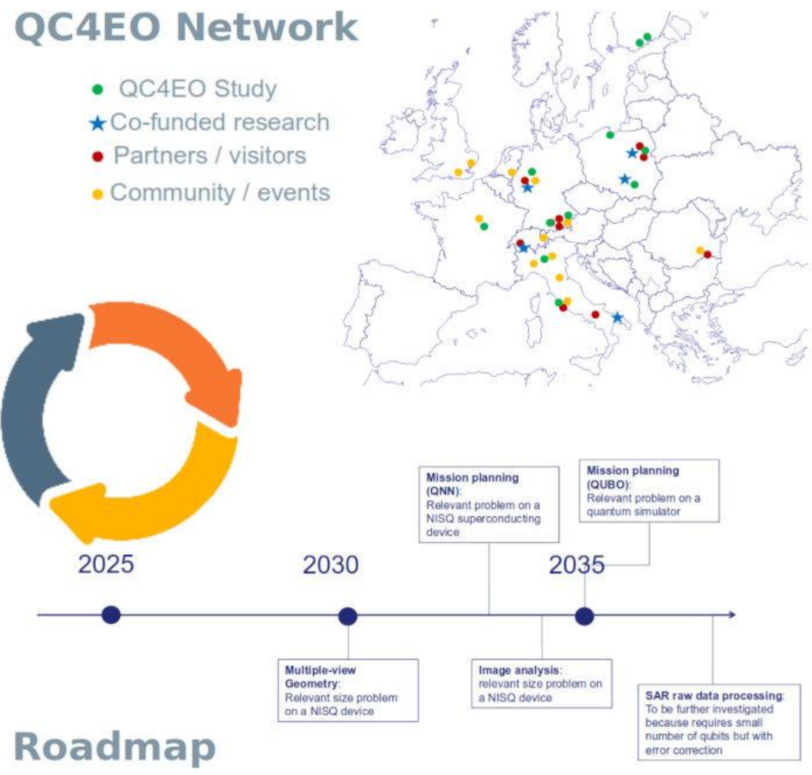
- ● QC4EO Study
- ★ Co-funded research
- ● Partners / visitors
- ● Community / events



Roadmap

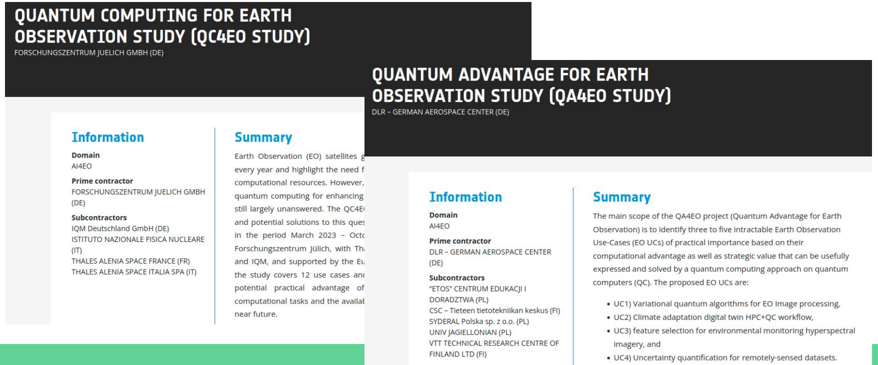
Φ-lab

QC4EO status



ESA's initiative to develop
the Quantum Computing
x Earth Observation ecosystem

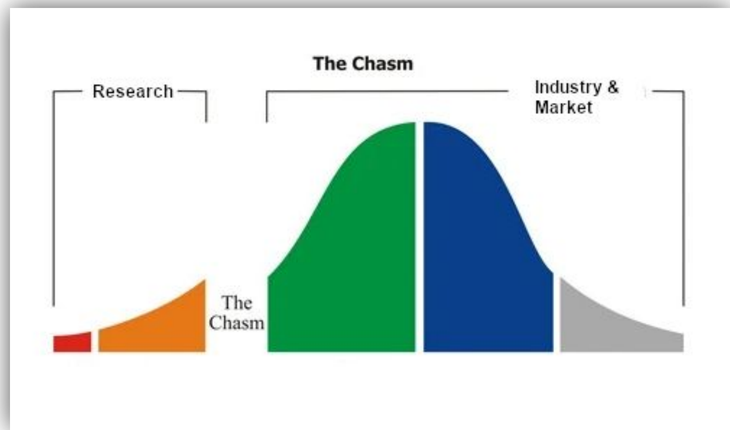
https://eo4society.esa.int/projects/qc4eo-study/
https://eo4society.esa.int/projects/qa4eo-study/
https://eo4society.esa.int/projects/quai4eo/



Various lines of research in QC

Academic research:

- Develop Q devices
  - Photonics...
- More qubits
- Fault-tolerant QC
- New Q Algorithms
- Optimisation on Q devices



Industry research:

- Develop Q devices
  - Digital (superconducting qubits)
  - Analog (annealer, neutral atoms...)
  - Digital-analog (trapped ion...)
- More qubits
- Develop agnostic hardware, software “layers”
- Develop Industrial Use-Cases... and claim advantage!
- Build ecosystems and markets, and align with global policies

Today’s talk

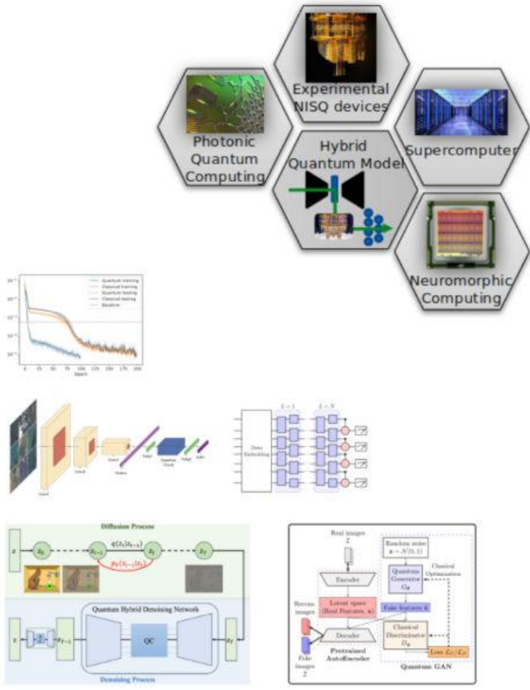
1. Motivation and status
2. Early steps in QC4EO
3. Recent advances in Quantum Machine Learning (QML) for EO
    a. Geometric QML
    b. Generative quantum AI
4. Challenges and Next steps

➔ Objective: giving an overview of research questions at the intersection of QC (mostly QML, but not only) and EO as an application

Early steps in QC4EO

Research questions at the beginning of QC4EO

- Is there any EO use-case fit for quantum physics?
  - No, mostly EO data, except maybe for quantum sensing
  - ➜ QC4EO is about quantum computing applied to classical data
- How to understand the potential of various QC algorithms?
- How to understand the potential of various quantum hardware?
- How small quantum (NISQ) can be applied to big real-life use-cases in EO?
- ~~What are the use-cases for which QC can bring an advantage?~~
  - ➜ Becomes: How to define a quantum advantage?



QML Research Sprints

Machine learning with quantum circuits

→ Hybrid classical-quantum neural network architectures

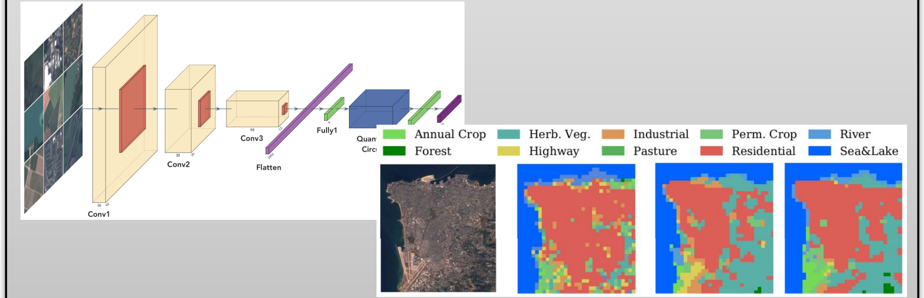
Case Study 1: Hybrid QCNN for EO classification

Use-case: EO image classification for land-use and land-cover.

Approach: Hybrid Quantum Classical CNNs enrich standard conv nets with a quantum layer!

Findings:

- Successful Proof of concept, with slightly better performances than comparable CNNs thanks to entanglement.



Sebastianelli et al. “On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification”, IEEE JSTARS (15) 2021

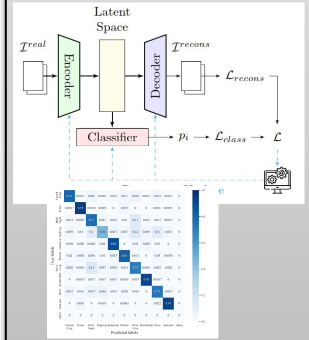
Case Study 2: Hybrid QCNN Expressivity

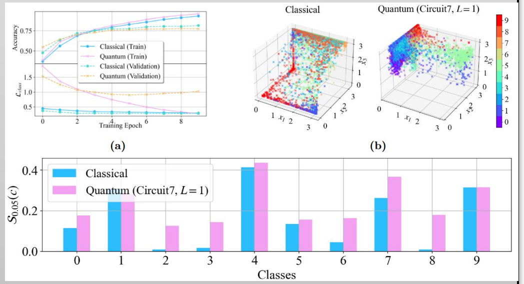
Use-case: EO image classification

Approach: Hybrid models with latent space embedding

Findings:

- Investigation of Quantum Ansätze: better expressivity with circuits with two-qubit SU 4 state
- End-to-end Proof of Concept for EO image classification with SOTA performances





Chang et al., “Quantum Conv Circuits for EO image classif.”, IGARSS 2022

Various quantum hardware

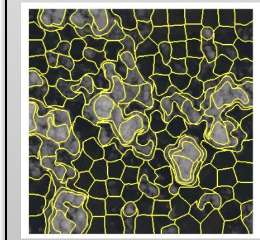
→ Annealing vs superconducting qubits?

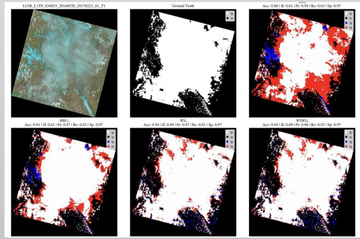
Case Study 3: Circuit-based Quantum SVM

Use case: cloud detection in multispectral EO images.
Approach: Hybrid Support Vector Machines (SVMs) with **gate-based quantum kernels**.

Findings:

- End-to-end pipeline to embed and process EO data with small NISQ circuits.
- Successful Proof of Concept, with results on par with standard SVM thanks to Quantum Kernel Target Alignment.





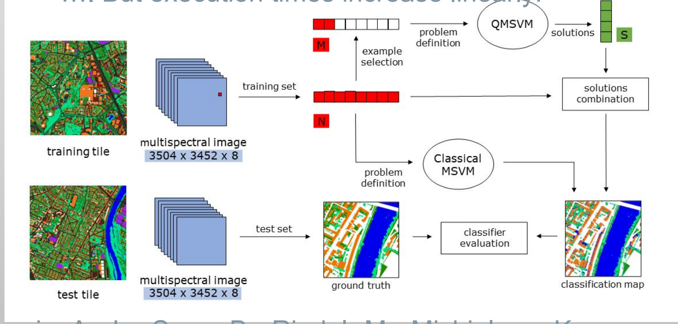
Miroszewski, A., Mielczarek, J., Czelusta, G., Szczepanek, F., Grabowski, B., Le Saux, B., & Nalepa, J. Detecting Clouds in Multispectral Satellite Images Using Quantum-Kernel SVMs. JSTARS (17) 2023

Case Study 4: Annealing-based Quantum SVM

Use case: Classification of multispectral EO data.
Approach: Hybrid Support Vector Machines (SVMs) with **Julich SC Quantum Annealer**.

Findings:

- Advantage Annealer operates only a limited number of samples for Q optimization…
- …. But execution times increase linearly!



Delilbasic, A., Le Saux, B., Riedel, M., Michielsen, K., & Cavallaro, G. A Single-Step Multiclass SVM based on Quantum Annealing for Remote Sensing Data Classification. JSTARS (17) 2023

How to define a quantum advantage?

➡ Intractable use-case, complexity reduction, or:

➡ generalisation power, faster learning, unforeseen advantage?

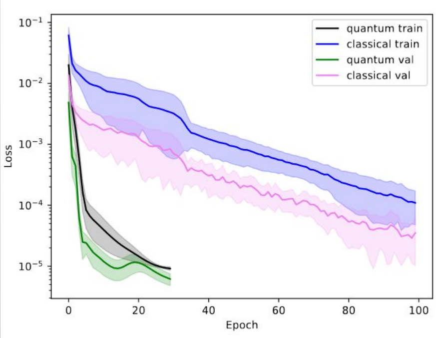
Case Study 7: Continuous-variable QC RNNs

Use case: Earth Systems observation and prediction.

Approach: Recurrent Neural Networks for time-series on Continuous-Variable QC.

Findings:

- Promises of faster training convergence
- For a small number of trainable parameters, it can achieve lower losses than its classical counterpart.



Siemaszko, McDermott, Buracsewski, Le Saux & Stobinska “Rapid training or recurrent quantum neural networks”, **QTML 2022 / Qu Mach. Intell. 2023**

UNIVERSITY OF WARSAW

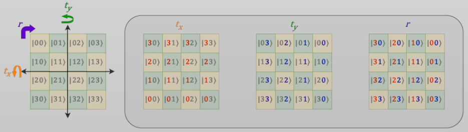
Case Study 8: Quantum Equivariant NN

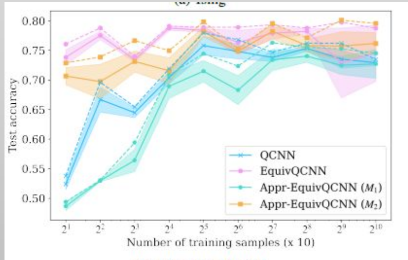
Use case: Data and image classification.

Approach: .design Quantum Neural Nets equivariant with respect to the underlying symmetry of the data to force inductive bias of the model.

Findings:

- Equivariance for planar wallpaper symmetry group p4m (reflections, 90d rotations)
- Equivariant design increases generalization power, in particular, while using only a small number of training samples
- Approximately- equivariant QNNs (with added noise) perform better on symmetric images.





(b) Extended MNIST

Chang et al., IEEE Quantum Week 2023

CERN

EPFL

Recent advances: Geometric QML

Research questions

Invariance / equivariance (by means of convolutions) are fundamental properties of modern neural networks, crucial to enable image or spatial processing

- Can we use the same properties to allow learning of bigger use-cases on small quantum devices?
- How does it impact the learning capacity of quantum neural networks?

Quanvolutional Neural Networks

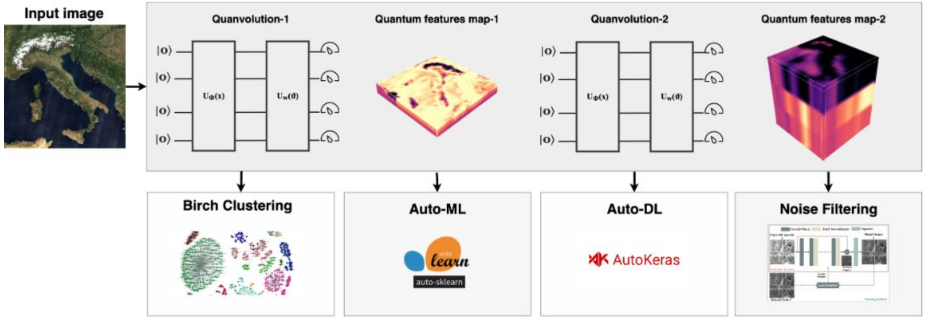
Objective: leveraging quantum for processing large volumes of multidim data

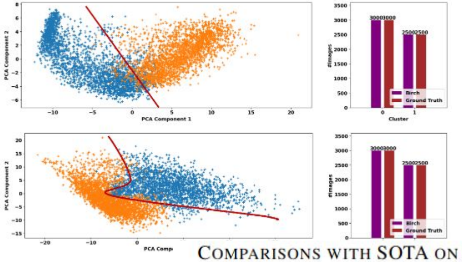
How? By learning **representations** (embeddings) with (Q)NNs

➔ Equals or improve by 5% classification in EO use cases wrt to classical approaches.

➔ reduced parameter size

➔ no training of quantum kernels (as in SVMs)





COMPARISONS WITH SOTA ON EUROSAT DATASET CLASSIFICATION

Model	Overall Accuracy	Model Size
Helber et Al. [34] ResNet-50	0.98	25 M
Helber et Al. [34] GoogleNet	0.98	7 M
Li et Al. [40] ResNet-18	0.98	11 M
Sumbul et Al. [41]	0.70	23 k
Sebastianelli et Al. [5] (Ry Circuit)	0.79	$42k + 4q$
Sebastianelli et Al. [5] (Bellman Circuit)	0.84	$42k + 4q$
Sebastianelli et Al. [5] (Real Amplitudes)	0.92	$42k + 4q$
Sebastianelli et Al. [5] (Coarse-to-fine grain)	0.97	$4 \times (42k + 4q)$
Quanv4Eo + Clustering	0.96	$16q$ (frozen)
Quanv4Eo + AutoML	0.91	$16q$ (frozen)
Quanv4Eo + AutoDL	0.93	$42k + 16q$ (frozen)

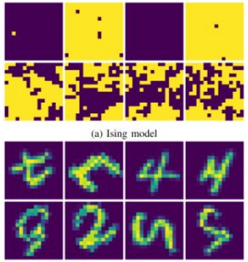
Quanv4EO: Empowering Earth Observation by means of Quanvolutional Neural Networkss

A Sebastianelli, F Mauro, G Ciabatti, D Spiller, B Le Saux, P Gamba and S Ullo

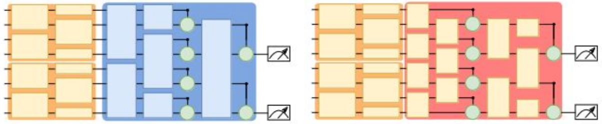
To appear 2024

Equivariant quantum neural networks

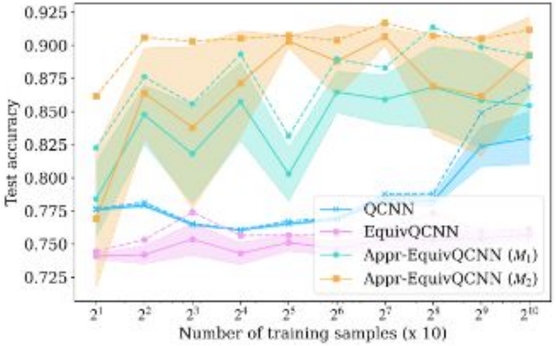
Bringing invariance to planar p4m symmetry, e.g. reflectional and 90◦ rotational symmetry.


(a) Ising model
(b) Extended MNIST

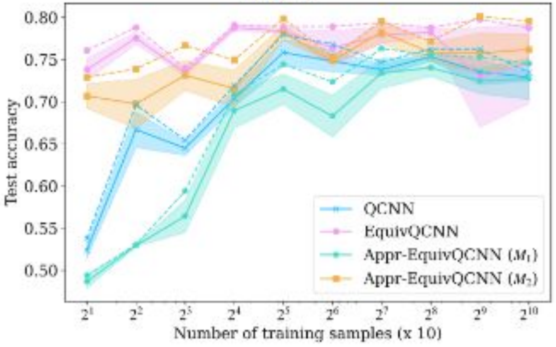
Building circuits with inherent symmetries:


(a) EquivQCNN (b) Appr-EquivQCNN

➔ increased generalisation power
➔ learns with less samples



(a) Ising



(b) Extended MNIST

[Approximately equivariant quantum neural network for p4m group symmetries in images]
SY Chang, M Grossi, B Le Saux, S Vallecorsa
2023 IEEE International Conference on Quantum Computing and Engineering (QCE)

Recent advances: Generative quantum AI

Research questions

Visual Generative AI (e.g. GPT-4, midjourney, etc.) is all the rage now.

Generative modelling comes at a higher cost (number of samples, parameters...) than discriminative modelling.

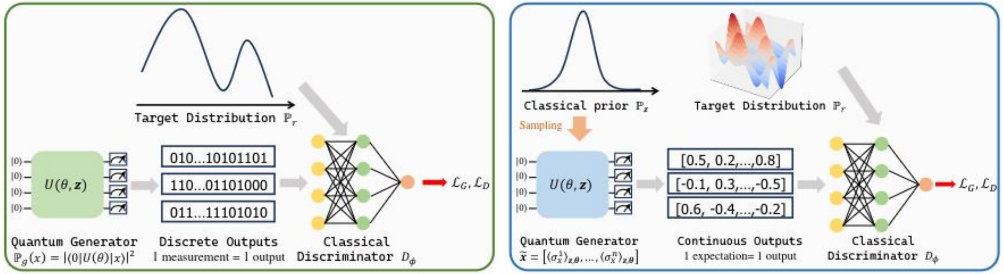
- Can we develop quantum versions of GANs or diffusion models?
- How do they compare?
- What kind of advantage appears?

Quantum GANs

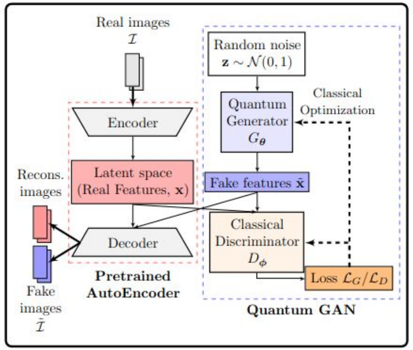
Approach: Quantum Generator + Classical Discriminator.

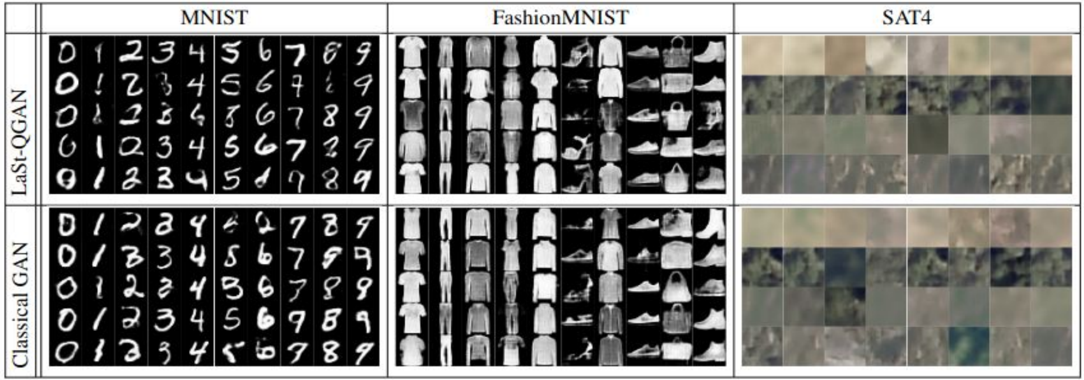
Findings:

- ➔ Trick #1: Latent space embedding by pretrained autoencoder
- ➔ Trick #2: Continuous, Style-based quantum GAN
- ➔ Successful image generation for varied image types
- ➔ Faster and better performances (in terms of distribution mapping) with less parameters



(a) Discrete Quantum GAN (b) Continuous Quantum GAN



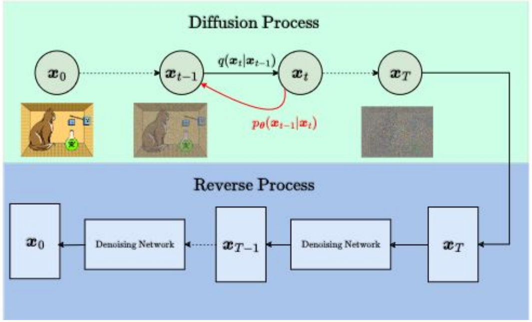


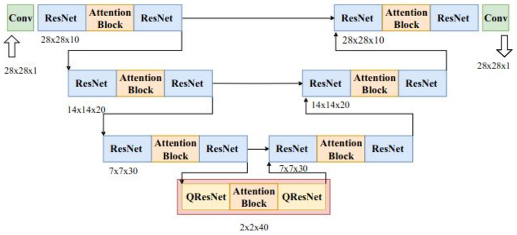
[Latent Style-based Quantum GAN for high-quality Image Generation](#) SY Chang, S Thanasilp, B Le Saux, S Vallecorsa, M Grossi, 2024 to appear

Quantum Hybrid Diffusion Models for Image Synthesis

- Standard Diffusion process
- Small step denoising learnt with a hybrid quantum/classical network: Quantum Vertex U-Net Hybrid Archi and variants

➔ Better-defined images much sooner with hybrid archi than purely classical!





Quantum Hybrid Diffusion Models for Image Synthesis F De Falco, A Ceschini, A Sebastianelli, B Le Saux, M Panella, Künstliche Intelligenz German Journal of Artificial Intelligence 2024

Quantum Latent Diffusion Models

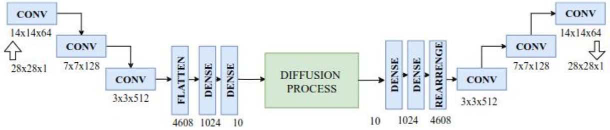
Encoding of images in a latent space and diffusion processed on embeddings

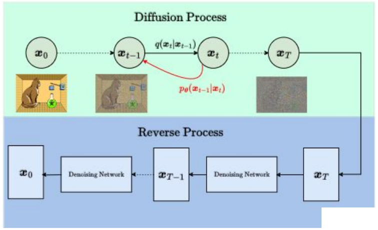
Metrics	Classical	BasicQ	3zQ	3xQ	4zQ	4xQ
Numbers of parameters	330	120	270	270	360	360
FID	44.3568	77.9277	43.4210	**40.4031**	43.3555	40.5321
KID	0.0368 ± 0.0013	0.0552 ± 0.0017	0.0333 ± 0.0013	**0.0318 ± 0.0010**	0.0361 ± 0.0013	0.0324 ± 0.0009
IS	1.8737 ± 0.0244	2.7361 ± 0.0449	**2.1717 ± 0.0216**	2.0002 ± 0.0287	1.9634 ± 0.0200	1.9736 ± 0.0209

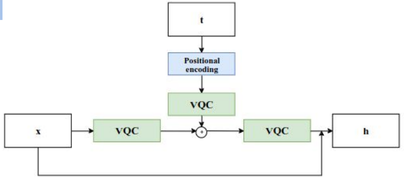
Table 1: Metrics of the images generated from the MNIST dataset

Metrics	Classical	BasicQ	3zQ	3xQ	4zQ	4xQ
Numbers of parameters	330	120	270	270	360	360
FID	90.3655	88.0443	85.8698	85.2147	**84.8859**	86.3102
KID	**0.0711 ± 0.0022**	0.0773 ± 0.0024	0.0734 ± 0.0022	0.0765 ± 0.0026	0.0754 ± 0.00224	0.0746 ± 0.0022
IS	**3.6283 ± 0.0701**	3.4746 ± 0.0735	3.4544 ± 0.0966	3.3330 ± 0.0599	3.4154 ± 0.0784	3.5169 ± 0.0617

Table 2: Metrics of the images generated from the Fashion MNIST dataset

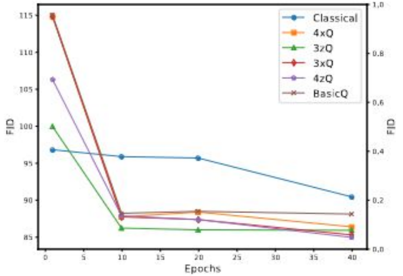


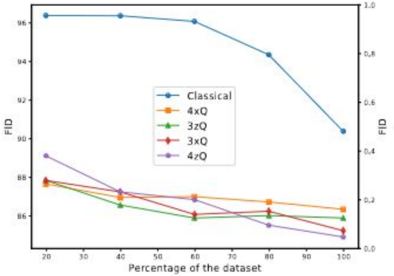




→ Results slightly better than classical DM with equivalent parameters

→ but convergence with less epochs and less samples!





Quantum Latent Diffusion Models F De Falco, A Ceschini, A Sebastianelli, B Le Saux, M Panella, to appear Quant. Mach. Intelligence 2024

Challenges and Next steps

Research questions now

- Which software developments?
  - In QML: optimisation and the curse of barren plateaus...
  - In QML: Quantum Graph Neural Networks
  - Beyond QML: combinatorial problem-solving algorithms
- How to push hybrid hardware modelling?
  - Modular quantum - supercomputing
- What other Earth-related questions can be modelled?
  - Climate interactions
- What other advantages could be studied?
  - Energy efficiency

Which developments needed in software?

Optimisation of QML circuits is made difficult by **barren plateaus** in the optimisation landscape = vanishing gradients in classical ML

Monitoring of variance of Loss of generator in QGAN ➔ enable to find parameters to avoid

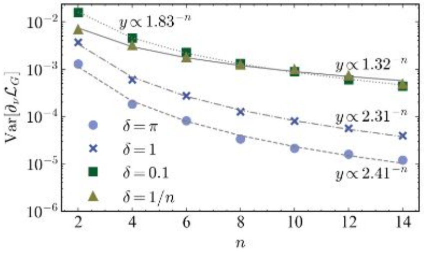


Figure 11. **Variance of the partial derivative of $\mathcal{L}_G$ versus the number of qubits n using logarithmic depth quantum circuit.**

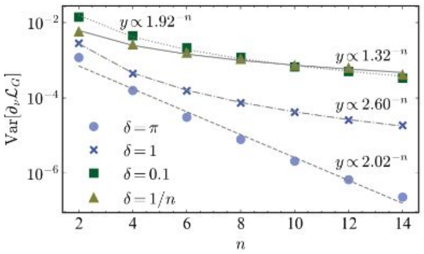
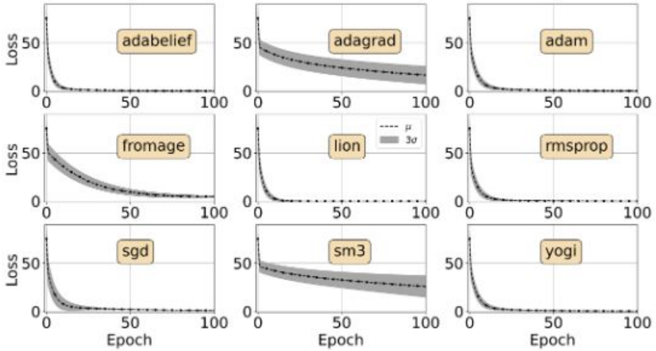


Figure 12. **Variance of the partial derivative of $\mathcal{L}_G$ versus the number of qubits n using polynomial depth quantum circuit.**

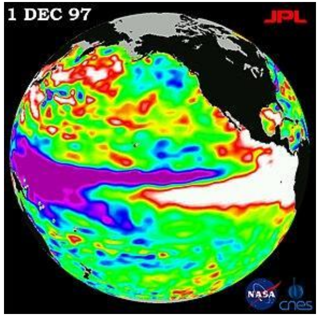
Evaluate various optimisers for a given task and grid search over parameters to test convergence



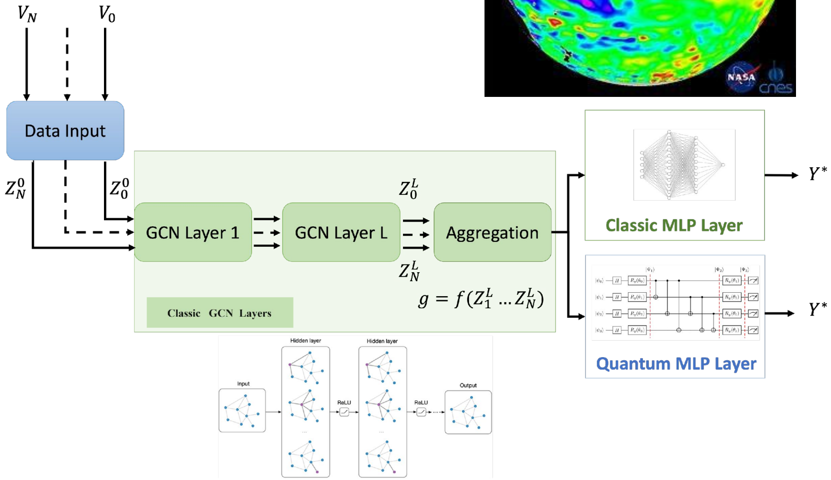
[Latent Style-based Quantum GAN for high-quality Image Generation](#) SY Chang, S Thanasilp, B Le Saux, S Vallecorsa, M Grossi, 2024 to appear

[On Hybrid Quanvolutional Neural Networks Optimization](#), S Mair, A Sebastianelli, A Ceschini, S Vidal, M Panella, B Le Saux, QTML 2023

Which developments needed in software?



Quantum Graph Neural Networks
For Climate interactions (El Nino effects SODA / GODAS datasets)



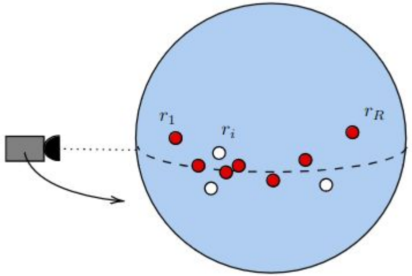
Surpassing state-of-the-art (SOTA) models with high efficiency and minimal training epochs.
QGraphino achieves all-season correlation skill of 0.975 in one-month prediction and 0.937 in two-month prediction.

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 Graph Neural Networks, F Mauro, A Sebastianelli, MP Del Rosso, P Gamba, B Le Saux, S Ullo, IGARSS 2024

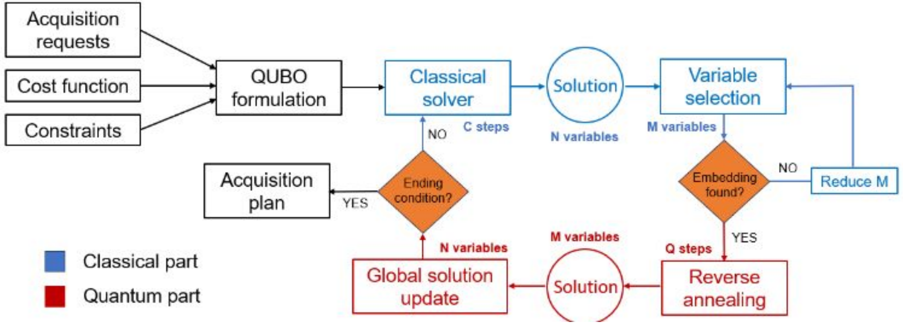
How to push hybrid software/hardware modelling?

- New algorithms for combinatorial problem-solving algorithms, e.g. in EO: mission planning



- Implementation in modular supercomputing environment, with quantum devices and cluster of computing nodes: How to distribute the tasks?

➔ Hybrid Quantum-Classical optimisation
➔ Reverse Quantum Annealing (allowing smart initialisation)



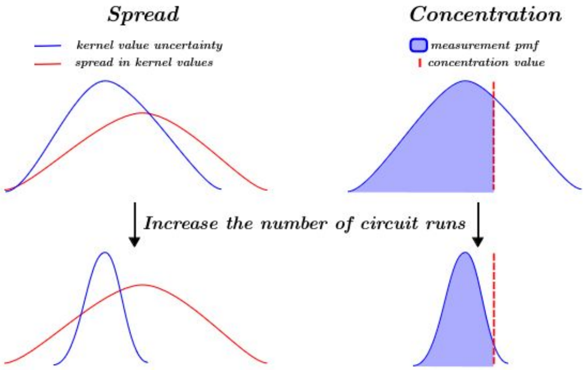
Reverse Quantum Annealing for Hybrid Quantum-Classical Satellite Mission Planning, A Delilbasic, B Le Saux, M Riedel, K Michielsen, G Cavallaro, IGARSS 2024

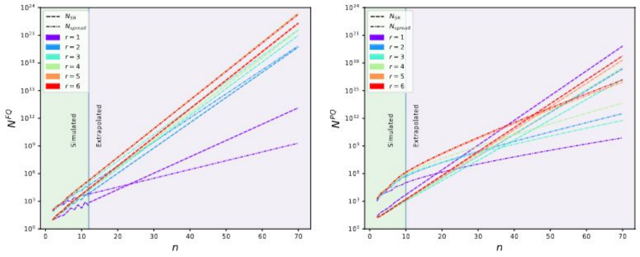
What other advantages could be studied?

Energy efficiency: quantum computer to run tasks with less impact on the earth resources

- Estimate number of circuit runs (shots) of a quantum algo by quantum resource estimation
- Proportional to compute time & energy consumption
- Heuristic to scale shot-nb estimation to non-simulable problems

➔ N grows exponentially with nb qubits for kernel methods :o(
➔ However, depends on kernel families and different data!
➔ There is a chance to find specific use-cases with suitable set-up :o)





Framework for number of shots estimation in quantum kernel methods, A Miroszewski, M Fellous Asiani, J Mielczarek, B Le Saux, and J Nalepa, arxiv 2024
Utility of quantum computing in remote sensing applications, A Miroszewski, B Le Saux, N Longépé, and J Nalepa, IGARSS 2024

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Quantum Computing for Earth Observation (QC4EO): Advances and Challenges in Generative AI and Quantum Neural Networks

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