Quantum Computing for Earth Observation (QC4EO) Study

Executive Summary

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Change Records

ISSUE	DATE	§ CHANGE RECORDS	AUTHOR
1	07/12/2023	First issue	FZJ

Table of contents

1 Scope of the document and terminology ... 4
1.1 Scope and context of the document ... 4
1.2 Reference documents ... 4
1.3 Acronyms ... 4
2 Study summary ... 6
3 Use cases summary ... 5
3.1 UC1: Mission Planning for EO Acquisitions ... 6
3.1.1 Instance for the quantum optimization approach ... 6
3.1.2 Instance for the quantum machine learning approach ... 8
3.2 UC2: Multiple-view Geometry on Optical Images ... 9
3.3 UC3: Optical Satellite Data Analysis ... 11
3.4 UC4: SAR Raw Data Processing ... 13
4 Conclusions ... 15

1 Scope of the document and terminology

1.1 Scope and context of the document

This document is a summary of the outcomes of the Quantum Computing for Earth Observation (QC4EO) study. You can refer to the study website[1] and the reference documents 1-4 for additional information.

1.2 Reference documents

[RD-1] QC4EO-D1-Use Case Definition and Design Report
[RD-2] QC4EO-D2-Machine Definition Report
[RD-3] QC4EO-D3-Machines Roadmap Assessment Report
[RD-4] QC4EO-D4-Use Cases Timeline Report

1.3 Acronyms

AR	Acquisition Request
BAQ	Block Adaptive Quantization
DLO	Downlink Opportunity
DTO	Data Take Opportunity
EO	Earth Observation
FFT	Fast Fourier Transform
InSAR	Interferometric SAR
IFFT	Inverse Fast Fourier Transform
FZJ	Forschungszentrum Jülich
MCF	Minimum Cost Flow
ML	Machine Learning
QC4EO	Quantum Computing For Earth Observation
QFT	Quantum Fourier Transform
QPU	Quantum Processing Unit
QUBO	Quadratic Unconstrained Binary Optimization
SAR	Synthetic Aperture Radar
SIFT	Scale Invariant feature Transform
SotA	State-of-the-Art
SVM	Support Vector Machine
TASI	Thales Alenia Space Italy
TASF	Thales Alenia Space France
TWMP	Tree Weighted Message Passing
UC	Use Case
VHR	Very High Resolution
WP	Work Package

[1] https://eo4society.esa.int/projects/qc4eo-study/

2 Study summary

Earth Observation (EO) satellites generate a growing amount of data every year and highlight the need for scalable algorithms and adequate computational resources. However, the question about how to leverage quantum computing for enhancing the required computational steps is still largely unanswered. The QC4EO study proposes insightful answers and potential solutions to this question. The study has been conducted in the period March 2023 - October 2023 by a consortium led by Forschungszentrum Jülich, with Thales Alenia Space Italy/France, INFN and IQM, and supported by the European Space Agency. The scope of the study covers 12 use cases and a 15-year timeframe, evaluating a potential practical advantage of quantum computing in specific computational tasks and the availability of the required hardware in the near future.

USE CASE TITLE	SHORT DESCRIPTION	BOTTLENECKS OF THE CONSIDERED CLASSICAL SOLUTION	PROPOSED QUANTUM SOLUTION
UC1: Mission Planning for EO Acquisitions	Finding an optimal acquisition plan of a satellite constellation given user requests	Acquisition planning is a combinatorial optimization problem of exponential complexity, currently solved with deterministic or heuristic methods	Two different approaches have been studied: quantum optimization and quantum machine learning
UC2: Multiple-view Geometry on Optical Images	Analyzing satellite images of a specific area captured from various perspectives	Keypoint extraction: combinatorial optimization problem of exponential complexity	Quantum clustering: quantum k-medoids, quantum kernel density
UC3: Optical Satellite Data Analysis	Analyzing the semantic content of satellite images	Kernel methods: quadratic algorithmic complexity and time overhead of kernel computation, expressivity of the kernel	Quantum kernels
UC4: SAR Raw Data Processing	Image generation of an area of interest from the raw signal received by the SAR system	Frequency-based methods (Range Doppler): polylogarithmic complexity of Fourier transformation	Quantum Range Doppler Algorithm

This study culminated in the release of four technical deliverables and an executive summary, each encompassing a detailed analysis of four selected use cases, i.e., mission planning for EO acquisitions, multiple-view geometry on optical images, optical satellite data analysis, and SAR raw data processing. The use cases have been selected according to their impact for the space industry and their compatibility with the expected development of quantum computing devices in the considered timeframe. For each use case, a relevant quantum algorithm is selected, a realistic problem instance is defined, and a timeline is proposed, mapping the problem size with quantum hardware requirements. Superconducting qubits and ion-traps are considered the most promising quantum computing technologies. The QC4EO study concludes that executing experiments on real hardware is expected to be possible for a reasonable problem size in the near future, providing practical insights on the theoretical advantage of the designed quantum algorithms.

3 Use cases summary

3.1 UC1: Mission Planning for EO Acquisitions

Mission planning is a pivotal aspect in EO, targeting the optimal scheduling of acquisition requests from end-users. State-of-the-art classical methods leverage deterministic and meta-heuristic algorithms to generate optimal solutions for smaller satellite constellations with thousands of optimization variables. However, as larger constellations featuring numerous satellites ($N \geq 100$) increases, the task of finding optimal solutions becomes more challenging. The difficulty is further intensified by the necessity to account for more complex mission constraints, impacting both the required time and the quality of the solution. Consequently, the concept of quantum advantage should consider not only the computational time but also the quality of the solution obtained. The QC4EO study proposes two distinct approaches to attack this problem: in the first one, the mission planning is cast into an optimization problem, while in the second approach relies on machine learning.

3.1.1 Instance for the quantum optimization approach

The objective of the mission planning is finding the optimal scheduling of satellite observations for a given list of user requests. For each satellite and for each "acquisition request", there are several "data take opportunities" and "downlink opportunities". The solution must return, for each satellite, a time-ordered shortlist of the possible observations and downlinks opportunities taking in consideration several constraints, i.e., on-board available memory, minimum preparation time between two subsequent acquisitions, time ordering of the acquisitions with respect to the downlink opportunities, available battery. We have formulated the problem in terms of a QUBO, where the original constraints now appear as penalty terms in a quadratic problem. We studied the feasibility of a quantum solution with the aim to improve the quality of the optimal solution. Our QUBO formulation is amenable for an implementation both on digital (or general purpose) quantum computer, using the Quantum Approximate Optimization Algorithm (QAOA), and analog specific-purpose quantum computers (or simulators) that are not able to

run generic quantum algorithms, but are optimized to solve specific problems, i.e., QUBO problems using quantum annealing algorithm in the case of QA. We underline the importance of proceeding in both directions: digital quantum computers have been recently applied to similar scheduling problems with a reduced set of variables and constraints; on the other hand, quantum annealers (and quantum simulators) can already allocate up to thousands of qubits and have shown promising results in the solution of similar optimization problems.
However, D-Wave states to be able to support real-world size applications with up to 1 million variables and 100,000 constraints via their quantum-classical hybrid solver: obviously, these numbers must be tailored on the specific problems based on the form of the interactions that appear in the cost function (including constraints).

	Problem size	**Hardware requirements**	**Timeline**		
			Up to 5 years	**Up to 10 years**	**Up to 15 years**
Minimum-size problem	2 satellites, 2.000 requests	Analog hardware (superconducting, neutral atoms): ~10^6 qubits (polynomial scaling of qubits). Digital hardware (superconducting): ~10^6 qubits (polynomial scaling of gates), error correction required	Problem implemented on NISQ devices	Problem implemented on NISQ devices	Problem implemented on NISQ devices
Full-size problem	10-100 satellites, 10.000-100.000 requests	Analog hardware (superconducting, neutral atoms): ~10^9 qubits (polynomial scaling of qubits), error correction required. Digital hardware (superconducting): ~10^9 qubits (polynomial scaling of gates), error correction required	No feasible implementation envisioned	No feasible implementation envisioned	Problem implemented if fully scalable error correction on superconducting devices become available

The QUBO approach to a medium real size mission planning problem involves 10^6 binary variables.
Although photonic platforms could potentially accommodate such a great number of qubits, we focused on forthcoming platforms such as superconducting qubits (digital quantum computers and quantum annealers), ion-trap digital quantum computers, and arrays of Rydberg atoms confined with optical tweezers. The main bottleneck for an implementation on quantum annealers (such as D-Wave Quantum Systems) is the required number of qubits, which depends both on the number of binary variables and the number of auxiliary qubits to account for the limited connectivity in the hardware. Our study anticipates that, while existing hardware can already manage very small size problems, it is feasible to solve at least the minimum-size problem (2 satellites, 2000 requests) within the 3 to 5 years. Our estimates are based on the D-Wave roadmaps, where they plan to reach more than 7000 qubits by 2024 with improved connectivity. Further, Rydberg simulators appear promising due to their intrinsic flexibility which allows for the adjustment of the connectivity to meet the specific requirements of each problem. On the other hand, the application of digital quantum computers appears feasible in a 5+ years horizon due to the number of qubits and gates required (see table below) even for a small-to-medium size problem. Since

QAOA is a hybrid-variational algorithm we expect that the implementation of error mitigation techniques will help the convergence towards optimal results. However, the timeline for solving the full-size problem for both approaches, general purpose quantum computers and quantum annealer-simulators extends beyond 15 years.

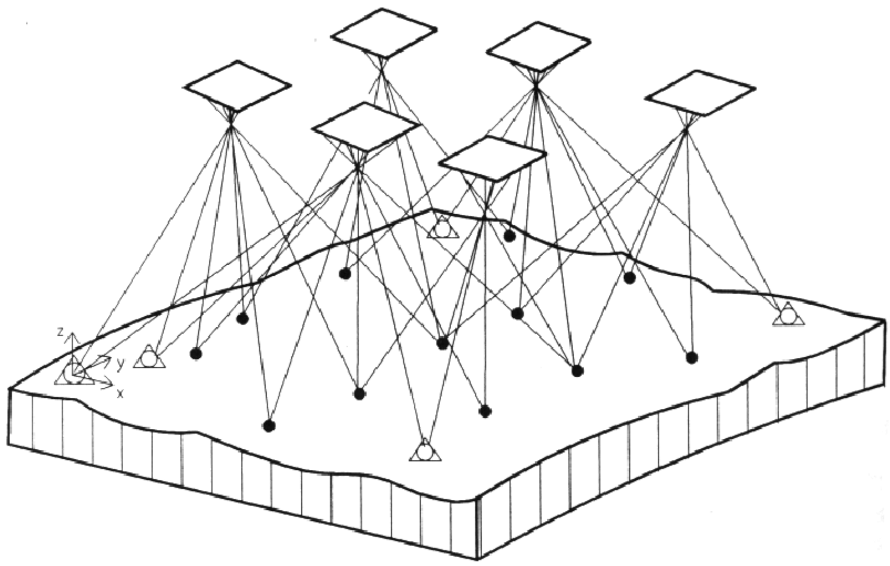
3.1.2 Instance for the quantum machine learning approach

In the second approach, the mission planning problem is addressed through a hybrid classical-quantum method based on a Quantum Neural Network (QNN) and a Reinforcement Learning (RL) framework. In this algorithm, an agent interacts with an environment, using a reward function to evaluate and assign values to the agent's actions. The RL agent employs a policy model to determine which actions based on the state of the environment, thus transforming the state itself. The policy model is trained to select actions that maximize the probability of achieving a positive reward. We considered the policy model as a parameterized quantum circuit to establish the input-output relation of the model and apply it within the mission planning context.

	Problem size	**Hardware requirements**	**Timeline**		
			Up to 5 years	**Up to 10 years**	**Up to 15 years**
Minimum-size problem	2 satellites, 2.000 requests	Accuracy related to number of features. Experimental demonstration with 32 features. Hardware requirements scale linearly: 2^f features encoded using 2^q qubits and 2^l layers with $f = q + l$.	Problem implemented on NISQ devices	Problem implemented on NISQ devices	Problem implemented on NISQ devices
Full-size problem	10-100 satellites, 10.000-100.000 requests	Accuracy related to number of features. Hardware requirements scale linearly: 2^f features encoded using 2^q qubits and 2^l layers with $f = q + l$.	No feasible implementation envisioned	No feasible implementation envisioned	Problem implemented if fully scalable error correction on superconducting devices becomes available

This quantum subroutine follows a classical pre-processing step based on classical neural network to reduce the number of relevant features, which serve as input for the QNN. This approach has demonstrated promising results for small-case instance and is viable for implementation on a general-purpose digital quantum computer. Specifically, the proposed quantum circuit requires few qubits (the exact count depends on the number of input data features) and few layers, yielding a number of logical gates that is linear with the input size. In previous work, a circuit with 4 qubits (thus encoding 32 features) and 8 layers, resulting in the implementation of more than 100 logical gates, was proposed to solve a small-medium size problem. This narrow quantum circuit can be already implemented on current state-of-the-art quantum hardware technology without full error-correction, such as IBM quantum computer based on superconducting qubits. Furthermore, IBM roadmap outlines the potential for hardware with over 4000 qubits by 2025, with plans for scaling to 10k-100k error-corrected qubits beyond 2026. This makes the implementation of the QML approach for the mission planning problem feasible within the next 15 years, even for full-size scenarios. The primary challenges in this algorithm stem from the error rates of quantum gates, which are device-dependent and significantly impact the quality of the obtained solution. In this context, it is worth to highlight another promising platform: trapped-ion based quantum computers. Despite having a smaller number of currently available qubits, these machines feature longer coherence times and notably lower error rates, often orders of magnitude below those of IBM processors. Furthermore, this technology provides enhanced connectivity compared to superconducting architectures. A notable player in this domain is the American public company IonQ, which has set ambitious plans to achieve 1024 qubits by 2028.

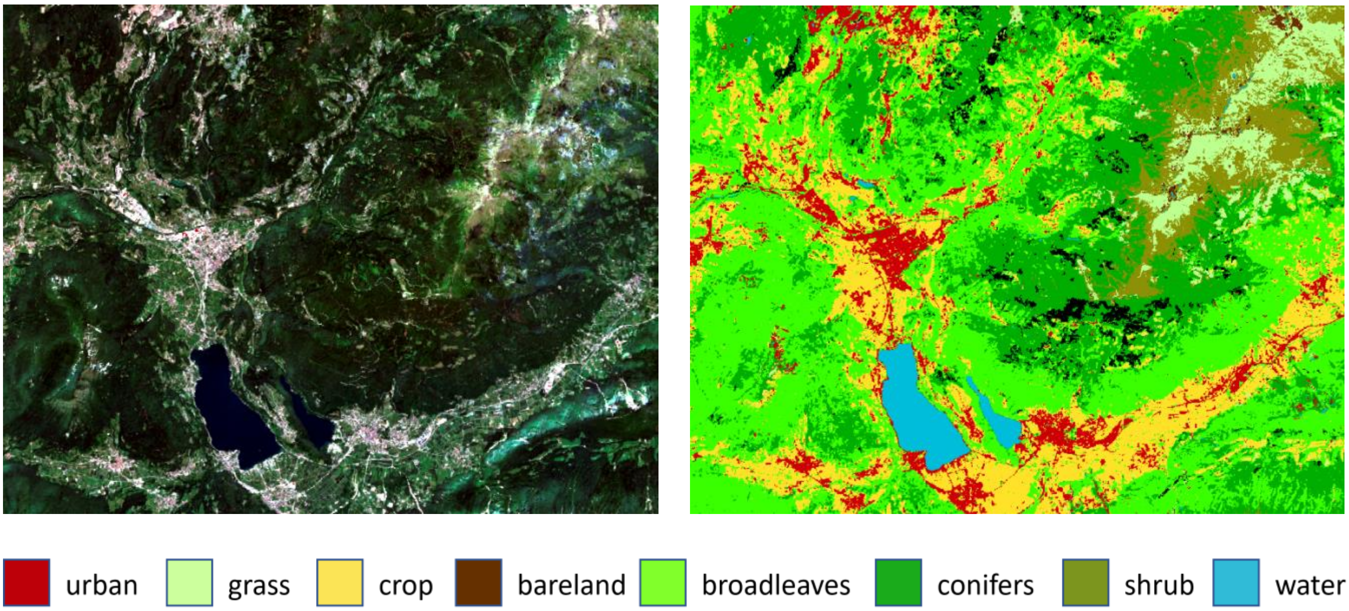
3.2 UC2: Multiple-view Geometry on Optical Images



Multiple images of a given area of interest can be retrieved as satellites orbit around the planet. These images may be obtained from different satellites or from a single satellite during a long enough opportunity window or multiple passes. An important task is to analyze the changes that have occurred on the area of interest as time has passed and perform terrain reconstruction. To do so, these images are compared with each other. However, the agility of the satellites and their different orbits result in the acquisition of different views of the area of interest: images may be rotated or translated, the illumination or scale may differ from one image to another. This problem can be tackled with bundle adjustment, which consists in estimating the different changes by minimizing the re-projection error, a single functional with a high number of parameters due to the high number of degrees of freedom. These calculations must be executed in a limited time to allow for more accurate approaches for terrain reconstruction and reduce constraints on the satellite platform localization. This method is conducted by first extracting keypoints that characterize well the different images, then by matching those that are common to multiple images. In this study, we have addressed the keypoint extraction and the feature matching problem using an optimization formulation and by utilizing both gate-based quantum computers and quantum annealers. The keypoints extraction procedure is conducted using two different clustering approaches: quantum k-medoids clustering and quantum kernel density clustering. In the first case, the problem is formulated as a Quadratic Unconstrained Binary Optimization (QUBO) to select k distinct objects located in the center of the image. In the second case, the problem is also formulated as a QUBO but the kernel matrix is computed by evaluating a quantum circuit on a gate-based quantum computer. Feature descriptors such as Scale Invariant Feature Transform (SIFT) are added to gain more information about the different scaling and rotations between images before performing the feature matching operation that uses quantum annealing as well as the kernel matrix computed a priori. We envision that ion-trap quantum computers and superconducting quantum computers and annealers are the most promising platforms for this use-case considering the needs for high qubit connectivity and for many qubits. The small size problem, which addresses images of tens of pixels, can already be solved efficiently using this quantum approach even though no clear advantage is demonstrated. However, extracting keypoints directly from the original image of a full-size problem would require a substantial number of qubits and high connectivity from the hardware architecture chosen. Such achievements seem unrealistic without scalable error corrected quantum computers and thus extend beyond 15 years. Nevertheless, an iterative approach that consists in solving the keypoint extraction problem on batches of medium-size images seems very promising. While the solution quality might slightly differ from that of the original approach, this process reduces greatly the resources needed for practical implementation on real hardware and may be possible within 5 to 10 years.

	Problem size	**Hardware requirements**	**Timeline**		
			Up to 5 years	**Up to 10 years**	**Up to 15 years**
Minimum-size problem	Extraction of 10 keypoints on 8x8 patches Feature matching of 10 keypoints	Analog hardware (superconducting, neutral atoms): 8x8 qubits. Additional digital hardware needed with 4 qubits.	Problem implemented on NISQ devices	Problem implemented on NISQ devices	Problem implemented on NISQ devices
Full-size problem	Extraction of 10 keypoints on 30.000x30.000 pixel images Feature matching of 10 keypoints	Analog hardware (superconducting, neutral atoms): 30.000x30.000 qubits. Error correction required. Additional digital hardware needed with 4 qubits.	No feasible implementation envisioned	No feasible implementation envisioned	Problem implemented if fully scalable error correction on superconducting devices becomes available

3.3 UC3: Optical Satellite Data Analysis



Optical satellite data analysis is indispensable for extracting valuable insights from acquired data, enabling the comprehensive study and enhanced understanding of terrestrial and oceanic processes, as well as Earth's dynamic systems. This encompasses crucial functions such as land cover monitoring, environmental assessment, precision weather forecasting, disaster preparedness and response, cutting-edge atmospheric research, and its application in diverse scientific and urban planning contexts. The QC4EO study focuses on the process of Land Use and Land Cover (LULC) classification, which aims at interpreting the information obtained by satellite data to create classification maps of the investigated scene. Classification maps are thematic products of great importance for many EO applications, such as monitoring deforestation, resource management, agriculture, and the study of the impact of climate change. This use case is addressed using quantum kernel methods. Kernel methods are a well-established framework in machine learning, and they can be understood as a two-step methodology. The first step involves mapping the data from the original input space into a higher-dimensional kernel feature space through a nonlinear function. The second step focuses on solving a linear problem within this transformed kernel space. These methods enable the design and interpretation of learning algorithms in the kernel space, which is nonlinearly related to the input space, effectively combining statistics and geometry. Importantly, they provide solutions with the desirable property of uniqueness, often requiring only a few sets of free parameters to ensure proper algorithm functioning. The mapping into quantum information is carried out by applying a data-dependent unitary transformation to an initial reference state. The circuit responsible for encoding, often referred to as the feature map, should be computationally challenging to simulate using classical methods; otherwise, it may not yield a quantum advantage. The quantum kernel function between two data points is obtained by taking the modulo square of the dot product between the quantum states obtained by encoding the corresponding feature vectors. Such a quantity cannot be directly calculated but must be estimated through a sampling procedure by performing measurements on the quantum state. The number of shots used to estimate each kernel function evaluation scales quadratically with the inverse of the additive error that one wants to achieve. To perform the training of the learning algorithm, it is necessary to evaluate the kernel function across all possible data pairs, and therefore, the number of such evaluations scales quadratically with the number of data points. The quantum kernel can then be used by classical supervised learning algorithms such as Support Vector

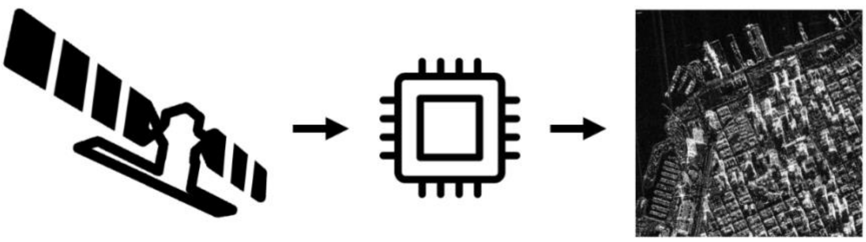
Machines (SVM) and Gaussian Processes (GP). These algorithms can be implemented on various quantum hardware platforms such as superconducting and trapped ion hardware. The number of qubits needed for this approach is strictly related to the number of features of data points, requiring a few hundred qubits for data with a high number of features (e.g., hyperspectral images, time series of data, etc.). The main obstacle for this approach is the computational time needed to calculate the kernel function evaluations between the data points. Access to quantum hardware resistant to errors is also important to obtain a good estimation of the kernel function. The QC4EO study anticipates that a full-size problem might be possible to solve within a 15-year timeframe. However, even though there are feature maps that are conjectured to be hard to simulate classically, it is not yet clear how the quantum kernel implementation might provide an advantage compared to classical solutions.

In the most common implementation of a quantum kernel algorithm, each feature from the data vector is encoded in a single qubit of the quantum register. Such encoding is carried out by applying some parametrized quantum gates whose parameters depend on the feature value, for instance by applying qubit rotation with an angle depending on the feature value. The encoding can be applied multiple times to increase the model's expressivity (data-reuploading algorithms). The number of required qubits is strictly related to the number of features in the data and amounts to about several hundred qubits for high-dimensionality hyperspectral data. The required qubits connectivity in the quantum hardware depends on the encoding strategy that is used: when using the so-called "full-entanglement" strategy a CNOT gate is applied to each possible pair of qubits, thus requiring full connectivity, however, there are
other possible entanglement strategy in which the CNOT gates are applied to a small subset of qubits pairs. To achieve a higher model's expressivity, the encoding should ideally be repeated several times thus increasing the circuit's depth. Such a higher depth will entail a higher number of gates and therefore error correction will be needed to ensure the correctness of the computation. Moreover, to estimate the kernel function value through a sampling procedure several run of the quantum circuits are needed. Such sampling procedure must be carried out for each possible data point pair (thus scaling quadratically with the dataset size). A low gate-operation time is therefore advisable in order to maintain the execution time low for a large problem with many image pixels. The two main quantum platform candidates for this application are superconducting qubits and ion-based quantum computers. Superconducting qubit hardware, such as those produced by IBM and IQM, provide, in general, a high number of physical qubits and a low gate time execution. The companies working with superconducting qubits have also plans to increase the number and the quality of qubits in the future: for instance, IBM is scheduled to provide a quantum computer with thousands of logical qubits in 2033. Ion trap quantum computers are another candidate for building quantum computing hardware: in general, they offer a higher connectivity and higher error fidelity when compared to some superconducting implementations, at the expense of a lower number of qubits. One of the main companies developing ion-trap quantum computing hardware is IONQ which currently provides quantum computer with a few tens qubit and it is planning to reach 1024 qubits in 2028, according to their technological roadmap.

The current estimated times for the execution of a 2-qubits gate on superconducting and ion-trap hardware are 533 ns and 50 ms, respectively. By considering those values, it is possible to get an estimate for the execution time of a problem instance on quantum hardware by multiplying the number of 2-qubits gates by their corresponding execution times. For this use case each quantum kernel instance must be calculated for each possible pair of data points, i.e., for on N(N-1)/2 values, with N being the number of pixels. For each of those values, the number of 2-qubits gates depends on the specific encoding structure, for example, when using a full entanglement scheme, it amounts to n(n-1) CNOT gates, with n being the number of qubits. The feature map can then be repeated by an arbitrary number of times L (data-reuploading models). Finally, for each kernel value to be estimated the circuit must run for a number of times that scales quadratically with the inverse of the average additive error that one wants to achieve. By taking these notions into consideration, it is possible to get an estimation of the number of CNOT gates and therefore the execution time.

	Problem size	Hardware requirements	Timeline
			Up to 15 years
Minimum-size problem	Learning problem with ~1.000 training samples	Digital hardware (superconducting, ion-trap): number of qubits fixed, equal to number of features (up to ~100), number of gates scales linearly/quadratically according to the entanglement scheme. Execution time has to be reasonably short	The problem can be implemented, but the feasibility depends on the gate times. The total time can be computed as described above. Currently, the execution time for a sufficient accuracy bound is prohibitive. As no roadmaps are available, no estimation can be provided for the future
Full-size problem	Learning problem with ~10.000 training samples	Digital hardware (superconducting, ion-trap): number of qubits fixed, equal to number of features (up to ~100), number of gates scales linearly/quadratically according to the entanglement scheme. Execution time has to be reasonably short	A time factor of 100 with respect to the minimum-size problem must be accounted

3.4 UC4: SAR Raw Data Processing



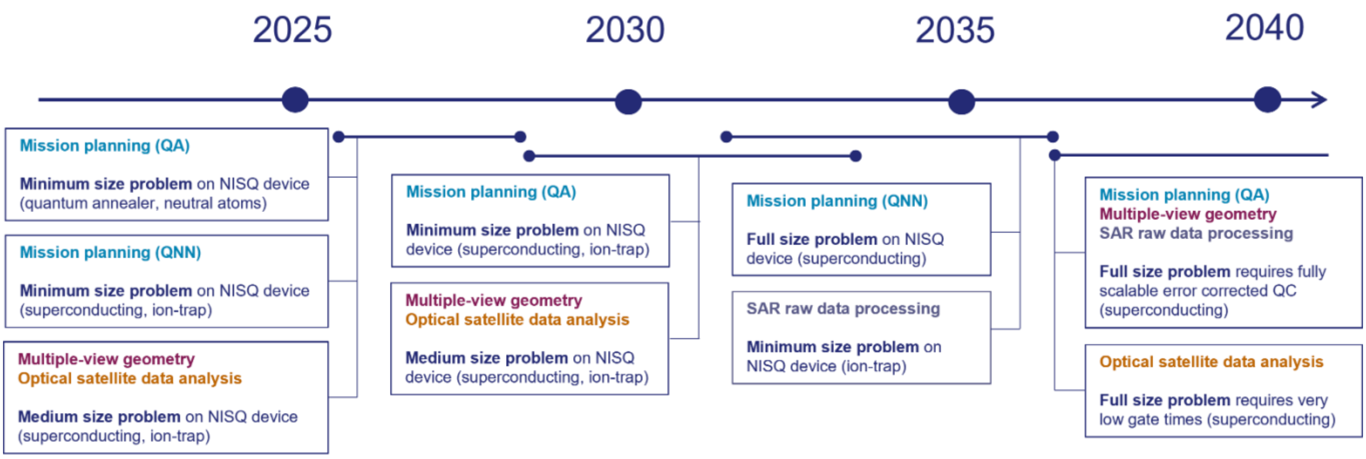
Synthetic Aperture Radar (SAR) is an active imaging technique that has had a significant impact on remote sensing, due to its effectiveness with different weather and lighting conditions. In SAR imaging, microwave signals are sent to the analyzed area by an airborne or spaceborne radar system. Then, the backscattered echo signals are collected and sampled by the radar. Image formation consists in generating an intensity image that gives a visual description of the physical properties of the analyzed area, starting from the acquired raw signal. A number of processing steps have to be performed, mostly related to the physical setting of the imaging system. The Range Doppler is a widely employed algorithm for this

purpose. Using the Fast Fourier Transform (FFT), the signal is transformed to the frequency domain, in which the processing steps are performed. This process is computationally expensive (FFT alone has time complexity $O(N\ log\ N\ )$) and challenging to extend to large-scale SAR acquisitions.
We proposed a quantum version of the Range Doppler algorithm based on the Quantum Fourier Transform (QFT). In theory, QFT provides an exponential speedup over FFT. However, a practical algorithmic speedup can potentially be achieved only when the whole processing pipeline is performed in the quantum domain, as repeatedly measuring the output of a QFT circuit hinders the algorithmic speedup. On the one hand, the required number of qubits would be relatively low, as it scales only logarithmically with the input signal size. On the other hand, the potentially very large circuit depth poses a challenge for NISQ devices, as it would require low gate error rates and long coherence times. Ion-trap devices may be able to solve a minimum size problem in the future, due to its better performance according to these requirements. Estimations still show a high error rate for ion-trap devices (IonQ) even for small-size problems. However, even an improvement in the error rate can lead to a breakthrough. For full-size problems, scalable quantum error correction is required, which can realistically be achieved only by superconducting devices. Optimistic forecasts envision this achievement within the next 15 years, also due to the low number of logical qubits required. Additional studies on the feasibility of the approach and its specific circuit implementation are crucial, as different formulations of the QFT can lead to different hardware requirements.

	Problem size	**Hardware requirements**	**Timeline**		
			Up to 5 years	**Up to 10 years**	**Up to 15 years**
Minimum-size problem	Image formation of a 16x16 patch (specific object and location)	Qubits scale logarithmically with the image size, while gates scale exponentially. Digital hardware (Ion-trap, superconducting): ~8 qubits, long coherence times and low error rates (not reached now)	No feasible implementation envisioned	Problem possibly implemented on ion-trap devices, according to the improvement in gate error rate	Problem possibly implemented on ion-trap devices, according to the improvement in gate error rate
Full-size problem	Image formation of a 10000x10000 patch (Sentinel-1 acquisition)	Qubits scale logarithmically with the image size, while gates scale exponentially. Digital hardware (Ion-trap, superconducting): ~27 qubits, very long coherence times and low error rates	No feasible implementation envisioned	No feasible implementation envisioned	Problem implemented if fully scalable error correction on superconducting devices become available

4 Conclusions

The QC4EO study provides an analysis of the exploitation of quantum algorithms and computing technologies for four selected use cases that hold high interest and impact in the domain of Earth Observation (EO). The main results regarding the expected predictions for effective usage of quantum computing are illustrated in the timeline. The tables show time predictions regarding the applicability of quantum computing to the use cases for different problem instance sizes. Some problems of small size, which are still distant from effective practical use, might be solved in a 3-5 year time frame. Full-size problems, on the other hand, are expected to be efficiently solved in at least 15 years, with improved, and possibly error-resilient, quantum computing hardware. It is important to point out, however, that these predictions were made considering the current knowledge of different quantum hardware platforms, and therefore, the actual possibility of efficiently solving the use-cases using quantum computing may change depending on future research findings.



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