Quantum Computing for Earth Observation

Use Cases Definition and Design Report

Written by	***Responsibility*** + handwritten signature if no electronic workflow tool
TASI Team	
Verified by	
Approved by	

Approval evidence is kept within the document management system.

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1 Scope of the document and terminology

The main objective of this document is to identify a list of Use Cases (UCs) for further examination in upcoming Work Packages (WPs). This is part of the effort of the project QC4EO study, which aims to create a roadmap detailing how and when Quantum Computing (QC) can significantly contribute to addressing challenging applications and computing tasks in Earth Observation (EO).

The methodology adopted by the consortium for establishing the final UC list is outlined in this document. It began with a "template" from which all partners, drawing on their expertise, proposed what is termed a "Scenario." In this context, a Scenario is essentially an initial overview of an EO problem, coupled with a collection of characteristic elements.

Following the submission of various scenarios, the consortium identified the top five most relevant ones. These chosen scenarios will be expanded upon, providing a more in-depth description of the related quantum algorithm and the specific architecture. These enhanced details will ultimately define the UCs, which are set to be further developed and refined in subsequent WPs.

The document is organized as follows:

- **Chapter 2** defines the perimeter of this analysis, reminding that the final shortlist is not exhaustive of the entire possibility offered by QC for EO; it also contains some other innovative scenarios that have not been considered in this study but for which there could be interest in applying QC.
- **Chapter 3** describes the information used to evaluate a scenario.
- **Chapter 4** contains all the identified scenarios.
- **Chapter 5** is the main output of this work, defining the shortlist of scenarios that will became UCs an so the quantum algorithms that will be studied in the next WPs; it also contains the motivations that lead to this selection and a comparison between the classical and quantum architecture (where we believe quantum computing could speed up the task).
- **Chapter 6** concludes the document by summarizing the main characteristics of identified UCs.

1.1 Applicable documents

[AD-1] QC4EO Study Statement of Work

[AD-2] Proposal submitted for QC4EO

1.2 Reference documents

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1.3 Acronyms

AR	Acquisition Request
BAQ	Block Adaptive Quantization
DLO	Downlink Opportunity
DPC	Displaced Phase Center
DTO	Data Take Opportunity
EO	Earth Observation
FFT	Fast Fourier Transform
InSAR	Interferometric SAR

IFFT	Inverse Fast Fourier Transform
ISL	Inter-Satellite Link
FTQC	Fault-Tolerant Quantum Computing
FZJ	Forschungszentrum Jülich
MCF	Minimum Cost Flow
ML	Machine Learning
NISQ	Noisy Intermediate Scale Quantum
PPO	Proximal Policy Optimization
PQC	Parametrized Quantum Circuit
QA	Quantum Annealing
QAOA	Quantum Approximate Optimization Algorithm
QC4EO	Quantum Computing for Earth Observation
QFT	Quantum Fourier Transform
QKE	Quantum Kernel Estimation
QNN	Quantum Neural Network
QPU	Quantum Processing Unit
QUBO	Quadratic Unconstrained Binary Optimization
RL	Reinforcement Learning
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

2 Perimeter of the Analysis

Earth Observation (EO) is an area rich in computational problems, and naturally, one wonders if new computing technologies like Quantum Computing (QC) could bring innovative solutions to these problems, unlocking a vast array of new and unexplored potentialities. However, this field is extensive and complex, with several use cases (UCs) existing in all parts of the EO pipeline. Given the limited time available for this study, one of the main challenges was defining all the possible UCs for QC applied to EO. This involved a trade-off between the number of UCs and the detail level of their descriptions. The risk of not covering potentially relevant EO UCs was mitigated by an interdisciplinary consortium, which offered a broad range of expertise, from raw data acquisition and processing to EO data analytics on the ground.

As mentioned in the introduction, a methodology for UC selection was devised, starting with the concept of a 'scenario' as a brief overview of an EO computational problem. What we report below is a list of potentially relevant scenarios that the consortium has identified as the most interesting EO problems to be solved to further improve the entire EO field. However, this list may not be exhaustive of the entire range of possibilities offered by the application of QC to the EO world. Given the field's vastness, it is possible that unexplored solutions exist for problems not included in our analysis perimeter.

This study primarily compares quantum solutions to identified problems against current strategies used to address them. This comparison is based on how consortium companies currently implement their solutions and how involved researchers have benchmarked their algorithms. However, other potential technologies for solving these tasks, such as AI, have not been extensively considered. They may have been taken into account, but only in a limited capacity.

With the goal of achieving meaningful outcomes, the consortium aimed to select pertinent scenarios encompassing all steps involved in any satellite-based EO mission, from mission analysis to data acquisition, processing, and data analysis. The result of this concerted effort is illustrated in Fig 1, which depicts these phases alongside a distribution of the identified scenarios, showing their correlation with the respective phases.

As can be seen, all phases are covered by at least one applicative scenario. Many fall in the ground raw data processing category (38%), while fewer have been identified for onboard raw data processing (15%). This distribution aligns with the difficulty of envisioning onboard quantum-based computations. A detailed description of the identified scenarios will be given in Chapter 4.

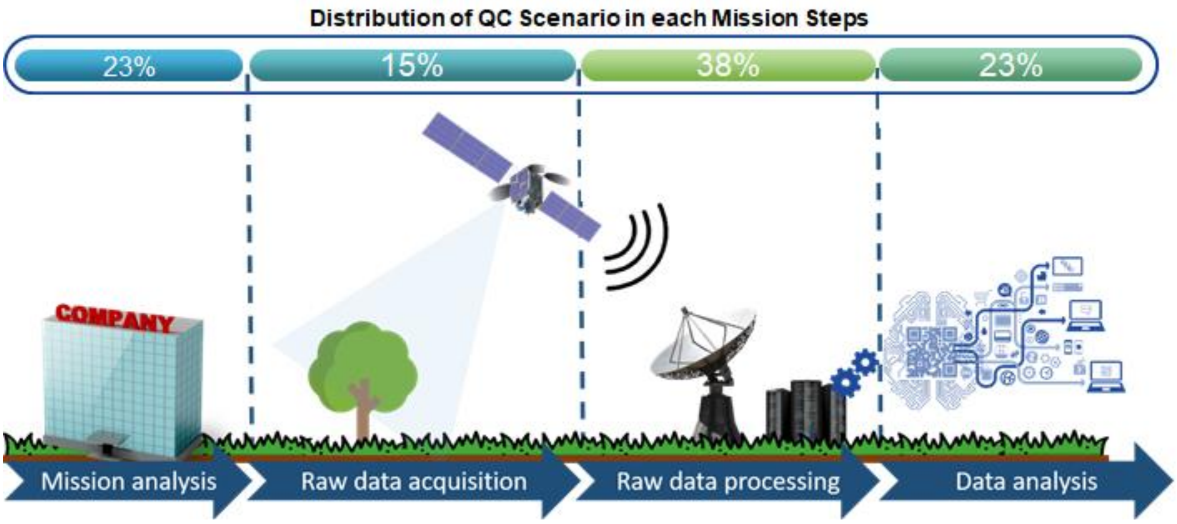


Fig 1 Mapping of Candidate QC scenario on the various steps of an EO mission.

3 Scenario description

This section describes the information used to describe the identified scenarios:

- **Problem's description**: a brief description of the problem in both words and mathematical formulation.
- **Impact on EO**: "high", "moderate", "minimum". It's the impact on EO that this problem could have If solved.
- **Mission step**: the step of the mission in which the problem emerges. It could be: mission analysis, data acquisition, data processing, data distribution and analysis.
- **Problem Sizing**: is an instance of the problem, indicating the typical size of it when applied to current EO systems. Both temporal and memory issues have been considered.
- **Bottlenecks**: current computational limitations (from a classical point of view)
- **Classical solution**: how the problem is currently tackled (state-of-the-art algorithms and their performances). This field explains how limitations are managed and what kind of approximations are involved.
- **Existing quantum solutions**: "yes" if the problem has already been studied from the quantum point of view, otherwise "no".
- **Potential quantum speedup**: if quantum solutions already exist, this field describes the potential quantum speedup to the problem; if "unknown", it has been difficult to quantify it or the problem has never been studied from the quantum perspective.
- **Level of quantum maturity within 15 years**: "small", "medium" or "high". It is the subjective level of confidence (an a priori assessment of the partner) that within 15 years the quantum solution will be so mature to target the full size problem or at least useful to be used in an hybrid approach, according to the following definitions:
    - small": very difficult that quantum solution could be implemented within 15 years;
    - "medium": it is likely that the quantum solution could be useful within 15 years but there are still fundamental challenges (both technical and conceptual) when quantum hardware is applied to the specific problem;
    - "high": it's very likely that the quantum solution could target the full size problem (or working as a dedicated QPU) because the only issue is scalability of current devices.
- **Bibliographic references**: references to the problem, both classical and quantum (if available) to be used by the reader for gaining more information on the problem.

4 Scenarios for Quantum Computing in EO

This section aims at defining the whole set of Scenarios identified by the partners of the Consortium. To this end, an iterative approach to progressively filter the most relevant has been pursued.

To expose such a process explicitly, we briefly present in the subsequent sections: the full list of preliminarily identified scenarios (section 4.1), the definition and characterization of those scenarios for which the scientific literature permitted to proceed further (section 4.2), described based on the just presented list of elements. Further Shortlisting of the Use Cases identified is then continued in chapter 5.

4.1 List of Candidate Scenarios

Within the consortium, with the leads of the Satellite operator companies, every partner exposed the set of candidate Scenarios that could possibly be of relevance in the field of Earth Observation. The following table lists all of those that have been preliminary identified by the consortium; not all of these have been detailed, as some of them lack scientific literature, or the expected timeline exceeds the considered 15-year period. Nevertheless, this makes them potential interesting innovative areas of application of QC to EO, so for the sake of completeness we added them to the list:

NUMBER	SCENARIO TITLE	GENERIC DESCRIPTION	BOTTLENECKS
1	Optical Satellite Data Analysis	See section 4.2.1	Algorithm-dependent. For kernel methods: expressibility and complexity of kernel computation ($O(N^2)$, N pixels).
2	SAR Raw Data Processing	See section 4.2.2	FFT complexity: $O(N \log N)$, N pixels.
3	Mission Planning for EO Acquisitions	See section 4.2.3.1	Exponential complexity of the optimization problem.
4	Multiple-view Geometry on Optical Images	See section 4.2.4	Exponential complexity of the optimization problem.
5	SAR Digital Beam Forming	See section 4.2.5	Complexity of solving a linear system: $O(N^3)$, N channels.

6	InSAR Phase Unwrapping	See section 4.2.6	Exponential complexity of the combinatorial problem.
7	SAR Image Segmentation	SAR images are completely different from optical counterparts and well-established computer vision techniques are not suited for segmentation task. The “speckle” effect and the special physical characteristics underlying SAR images, make important to develop hybrid approaches and towards this direction it will be interesting to evaluate if quantum algorithms can give a performance increase.	Algorithm-dependent.
8	Optical and Radar Data Fusion	Exploiting quantum algorithms for processing optical and radar views of the same scene, improving feature extraction capabilities and consequently classification and analysis. Image fusion techniques proved to enhance the quality of SAR images when combined with optical images.	Algorithm-dependent, polynomial complexity.
9	SAR Co-registration	Co-registration is the alignment of SAR images from two antennas and is an essential step for the accurate determination of phase difference and for noise reduction. It is strictly related to image alignment task.	Cross-correlation computational complexity: $O(N^2)$, N pixels.
10	SAR Antenna Design Optimization	Using of quantum computing algorithms for improving resolution of partial differential equations for electromagnetic simulation could improve EO system by helping both in the design of antennas and simulating the radar response of complex ground scatterers	Exponential complexity of the optimization problem.
11	SAR Raw data Compression	Exploiting hybrid quantum\classical schemes for data compression could be crucial for next generation SAR systems. A lot of works exist in classical ways to improve on-board data compression like for example FFT-BAQ.	Algorithm-dependent, polynomial complexity.
12	Large Constellation Design	QC for design optimization of large constellations.	Exponential complexity of the optimization problem.

The above-mentioned list of Scenarios are mapped into the satellite mission data pipeline as follow:

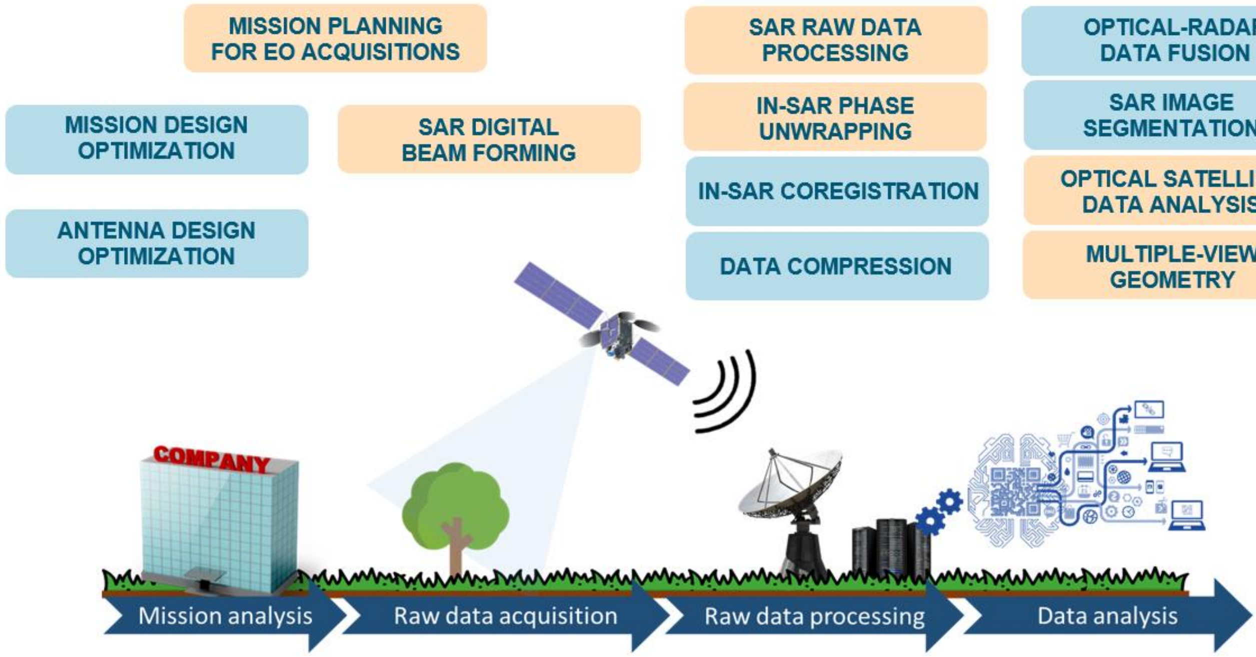


Fig 2 Scenarios Mapping over Mission Steps. Highlighted scenarios are those that have been furtherly investigated in this work and from which the final shortlist of Use Cases has been generated

4.2 Shortlist of the Candidate Scenarios

Not all of the above identified scenarios are equally covered in the literature: some of them are completely new, meaning that the idea of applying QC to these problems is coming for the first time from this consortium, while others have only a limited number of publications. So, mainly based on the number and quality of the existing works and considering the time horizon required for this study (15 years) we only selected a subset of them to further study.

The following scenarios are those that have been investigated by the consortium, ordered by their potential impact on EO applications:

1) Optical Satellite Data Analysis
2) SAR Raw Data Processing
3) Mission Planning for EO Acquisitions
4) Multiple-view Geometry on Optical Images
5) SAR Digital Beam Forming
6) InSAR Phase Unwrapping

4.2.1 Scenario n° 1: Optical Satellite Data Analysis (FZJ)

Problem's description: Optical satellite data analysis plays a crucial role in various sectors, serving diverse purposes. One of the essential tasks is land cover classification (at pixel level), that is to categorize and interpret the information obtained from satellite sensors, converting it into meaningful and actionable insights about Earth's surface features and phenomena. One relevant EO application is the production of frequently updated thematic products. Most of them are maps that represent the spatial distribution of identifiable Earth surface features classified in classes [RD-3]. They can be associated to land cover classes (i.e., physical objects that occupy the surface of the Earth, e.g., crop types, kinds of buildings, types of water bodies, etc.) or to land-use classes (i.e., to describe the use of the land surface by humans, e.g., farming fields, industrial areas, etc.).

I**mpact on EO**: High. Optical satellite data analysis provides crucial data for promoting environmental sustainability and facilitating development. Furthermore, it is invaluable for environmental monitoring, enabling us to monitor global changes like deforestation [RD-4], desertification, and indicators of climate change [RD-5]. During natural disasters, satellite imagery becomes a lifeline by offering real-time data for disaster management and assessment. It also supports urban planning efforts by informing infrastructure development and helping assess environmental impacts [RD-6]. Resource management, including water, minerals, and wildlife populations, benefits from satellite imagery, enabling optimal exploration and conservation practices. In the agricultural sector, it aids precision farming by monitoring crop health, irrigation, and predicting yields [RD-7]. Satellite imagery is pivotal in studying the impacts of climate change, monitoring factors such as sea levels, temperature, and atmospheric changes. Moreover, it supports navigational needs, mapping updates, and contributes to scientific research in disciplines like geography, geology, oceanography, and astronomy. Ultimately, Optical satellite data analysis plays a vital role in addressing a wide range of global challenges and enhancing our scientific understanding.

Mission step: data processing

Problem sizing: The complexity of land cover classification problems is influenced by a variety of factors. These include the type of data source used, whether that be a single-date image or a time series analysis. The type of satellite sensors employed also contributes significantly to the complexity, as does the scope of the study area, which could range from a single region to an entire country, or even to a continental or global scale. The availability of labeled training samples, which is crucial for supervised learning methods, can also determine the difficulty of the task. Finally, the classification system used, i.e., the specific types of land cover classes, will also influence the scale of the problem. See section 5.4.4 for an example of a problem instance.

Bottlenecks: For the training phase over a dataset of size N, Kernel methods require the construction of the Gram matrix which requires O(N^2) kernel function evaluations, i.e., the kernel function evaluations between all pairs of training data points. The required operational complexity for the training phase depends on the algorithm considered: for instance, for gaussian processes the main operation consists in the inversion of the Gram matrix of size NxN, whereas the training of support vector machines amounts to the optimization of a constrained quadratic problem of N variables. It is important to point out that, In the quantum kernel implementation considered in this work, such complexities are inherited by the quantum kernel since it does not modify the structure of the algorithm but rather how the kernel function is evaluated. Therefore, potential quantum advantages should be investigated in how the quantum kernel function itself might provide some utility over the classical one.

Classical solutions: The surge in the availability of satellite data, combined with advancements in machine learning [RD-9] - particularly deep learning [RD-10] - has driven the development of sophisticated land cover mapping systems. These systems adeptly harness information derived from time series of remote sensing imagery. The choice of analytical methods can range from traditional machine learning techniques, such as Random Forest (RF) and Support Vector Machine (SVM), to more recent deep learning approaches like Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Transformers. In this study, we focus on solutions created using kernel methods, namely Support Vector Machines (SVMs) and Gaussian Processes. Despite being less popular than deep neural networks - likely due to hardware advancements favoring deep learning - kernel methods have proven their worth. They have been extensively utilized in the analysis of optical satellite data, achieving remarkable results across a variety of EO applications.

Existing quantum solutions: Some initial works have already been proposed in the literature that develop machine learning models employing Parametrized Quantum Circuits (PQC), which are quantum circuits whose gate operations are determined by some parameter values. The main class of algorithms employing PQC in Quantum Machine Learning are Quantum Kernels [RD-11] and Quantum Neural Networks (QNN) [RD-12]. Both models use a combination of quantum and classical information processing. Such hybrid models are the most widely studied models in the current NISQ era.

- *Quantum Kernel*: In this setting the objective is to use Quantum Computing methodologies to implement a kernel function that is then used with classical ML kernel methods such as Support Vector Machines (SVM) or Gaussian Process (GP). Specifically, a PQC is used to encode a feature vector **x** in the quantum state $|\phi(\mathbf{x})\rangle$ through the application of a data-dependent unitary $\mathcal{U}_{\mathbf{x}}$ to the initial state $|0^{\otimes n}\rangle$, i.e. $|\phi(\mathbf{x})\rangle$=$\mathcal{U}_{\mathbf{x}}|0^{\otimes n}\rangle$. The kernel function evaluation between two feature vectors **x** and **y** is calculated by considering the fidelity between the quantum states $|\langle\phi(\mathbf{x})|\phi(\mathbf{y})\rangle|^2$.

- *Quantum Neural Networks*: In the literature the term QNN refers to a Quantum Machine Learning framework that employs a PQC whose parameters are variationally optimized with respect to a specified cost function with a classical computer. In hybrid quantum-classical Neural Networks the PQC is used as a component in a data processing framework alongside classical information processing. For instance, in [RD-13] and [RD-14] a hybrid workflow using both classical NN processing and PQCs was applied to remote sensing images classification.

Potential quantum speedup: To have a quantum advantage a quantum kernel must not be easily simulated by a classical system. For instance, [RD-15] proposed a quantum kernel with a circuit feature that is conjectured to be hard to simulate classically. The second point to be addressed when considering potential quantum advantages over the usage of classical well-known kernels is whether a quantum kernel provides some kind of improvements in terms of performances with respect to a classical one. In [RD-16] and [RD-17] it was shown that, for some specific engineered learning problems with data having a specific structure, the usage of a quantum kernel provides some advantage over the usage of a classical one. However, whether and how EO-relevant tasks can benefit from the usage of quantum kernels is still an active area of research.

Level of quantum maturity in the next 15 years:

The main limitation for current quantum computing applications is the availability of reliable large-scale error-corrected quantum hardware. The current state of quantum computing hardware is referred to as NISQ (Noisy Intermediate Scale Quantum) [RD-8] in which the current quantum devices consist of a limited number of noisy qubits with a limited coherence time. The number of qubits in the devices being manufactured is increasing and is expected to grow in the upcoming years as well. However, there are some physical issues to be addressed in order to guarantee the quality of the results provided by these devices.

Bibliographic references: RD-3, RD-4, RD-5, RD-6, RD-7, RD-8, RD-9, RD-10, RD-11, RD-12, RD-13, RD-14, RD-15, RD-16, RD-17

4.2.2 Scenario n° 2: SAR Raw Data Processing (FZJ)

Problem's description: Synthetic Aperture Radar (SAR) is an active imaging technique that has had a significant impact on remote sensing. 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. Several compression and correction steps have to be performed, which consider the physical setting of the imaging system.

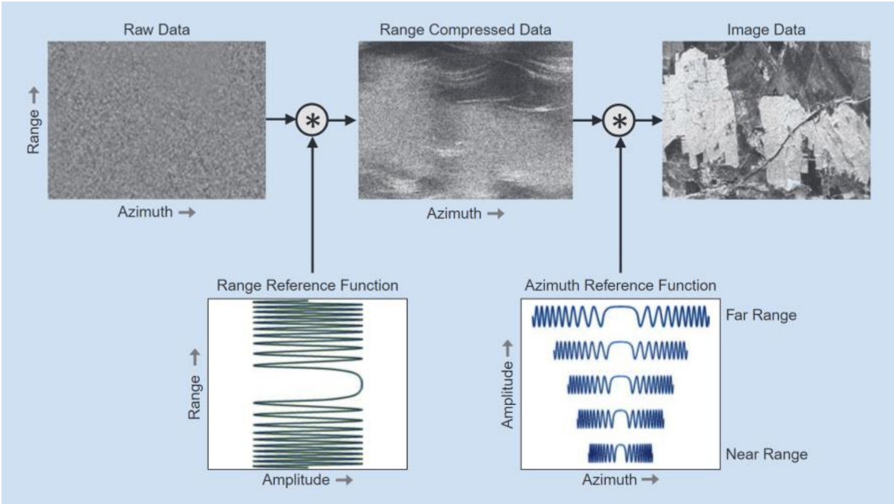


Fig 3 summary of a simple SAR processing pipeline [RD-18].

Impact on EO: High. SAR is a highly relevant technology in EO. Multiple SAR missions have been launched in the last few years. It is used to collect information in a wide range of applications, regardless of illumination and weather conditions. SAR raw data processing algorithm (focusing of SAR images) is currently one of the main important bottlenecks to move information extraction on-board. Not only, because of the complex nature of these data, phase information can enable highly impacting applications like SAR interferometry for geophysical monitoring of natural hazards (for example earthquakes, volcanoes, and landslides) and in structural engineering, in particular monitoring of subsidence and structural stability. So, it is of crucial importance try to understand if alternative ways of processing this information are possible; indeed, for enabling on-board processing, not only a speedup in time but also a reduction in mass and energy consumption is needed.

Mission step: data processing.

Problem Sizing: in standard methods, the image formation algorithm requires the computation of multiple Fast Fourier Transform (FFT) steps applied to the sampled signal $s(\tau,\eta)$ both in the range (τ) and azimuth (η) domain. Time performance depends on multiple aspects, e.g., extension of the analyzed area, bandwidth, chosen sampling, chosen algorithm. Raw data matrix can achieve the size of 10000 samples (range) x 30000 lines (azimuth), giving a total amount of 10000*30000*2= $6*10^8$ real values to be stored and processed.

Bottlenecks: heavy computational burden for large images. FFT has a complexity of $O(N\,log(N))$.

Classical solution: multiple SAR image formation algorithms are available in the literature, which differ in time performance and image quality [RD-19]. The first algorithm designed for spaceborne image processing is the Range Doppler Algorithm (RDA). The current algorithm used for generating Sentinel-1 higher level products is based on RDA. The basic implementation consists in the following steps:

- Range Compression: a range FFT is performed on the raw signal $s(\tau,\eta)$, a frequency domain matched filter $G(f_\tau)$ is multiplied and the range inverse FFT is applied;

$$s_{rc}(\tau,\eta) = IFFT_\tau[FFT_\tau[s(\tau,\eta)]G(f_\tau)]$$

- Azimuth FFT: an azimuth FFT is applied to the obtained signal;

$$s_1(\tau,f_\eta) = FFT_\eta[s_{rc}(\tau,\eta)]$$

- Range Cell Migration Correction: a compensation added to signal, since the distance between points on the ground and the receiving antenna (e.g., the slant range) is not constant, due to the azimuth movement of the platform. For small slant angles, RCMC can be implemented as an FFT, linear phase multiplier $G_{rcmc}(f_\tau)$, and IFFT [RD-26];

$$G_{rcmc}(f_\tau) = exp\left\{j\frac{4\pi f_\tau \Delta R\{f_\tau\}}{c}\right\}$$

- Azimuth Compression: a frequency domain matched filter $H_{az}(f_\eta)$ is multiplied and the azimuth inverse FFT is applied.

$$s_{ac}(\tau,\eta) = IFFT_\eta[S_2(\tau,f_\eta)H_{az}(f_\eta)]$$

Existing quantum solutions: no.

Potential quantum speedup: unknown. The idea behind this study is to understand if it's possible to realize a sort of a quantum version of the classical Range Doppler Algorithm by leveraging on the 1D QFT algorithm. It is known that the QFT does not offer a direct quantum speedup compared to FFT [RD-20]. In addition, the encoding of classical data into quantum data brings an additional practical computational overhead. However, a speedup can be achieved by incorporating multiple classical processing steps in a more complex quantum circuit and exploiting the quantum representation of data.

Level of quantum maturity within 15 years: medium. The development of superconductor quantum computers is expected to reach a higher level in terms of quantum volume, which can increase the size of the problem. However, the feasibility of integrating on-board quantum computing technology is still an open question, as previous studies are limited to quantum communication.

Bibliographic references: RD-18, RD-19, RD-20, RD-26

4.2.3 Scenario n° 3: Mission Planning for EO Acquisitions

This problem has been tackled independently by both TASI-INFN and TASF teams. Because the importance of the topic and the fact that two different approaches have been pursued, leading to two different quantum alternatives, we decided to report both implementations of the same problem as two different scenarios.

4.2.3.1 Scenario n°3.1: TASI-INFN formulation

Problem's description: the mission planning problem deals with the optimal scheduling of satellite observations for a given list of user requests (knapsack problem). Indeed, for each satellite and for each "Acquisition Request" (AR) there are several "data take opportunities" (DTOs) and "downlink opportunities" (DLOs): the optimizer must return a time ordered short-list of those observations and downlinks that are possible when several constraints are taken into account (Fig 4). Mathematically, this is a combinatorial optimization problem characterized by the following cost function:

$$F(\vec{x},\vec{y}) = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{\theta_{i,j}}\sum_{r=1}^{\sigma_i}\left(\alpha t_{i,j}^{k} x_{i,j}^{k} + \beta s_{i,j}^{r} y_{i,j}^{r} - \frac{\gamma}{m} x_{i,j}^{k}\right)$$

where the decision variables $x_{i,j}^{k} \in \{0,1\}$ and $y_{i,j}^{r} \in \{0,1\}$ are binary variables describing the DTOs and the DLOs respectively: if the AR j is scheduled by satellite i at the opportunity k, then $x_{i,j}^{k} = 1$; otherwise $x_{i,j}^{k} = 0$, and similarly for the DLO variables $y_{i,j}^{r}$. The following parameters appear in the above cost function as inputs to the optimizer:

- $n \in \mathbb{N}$ the number of satellites;
- $m \in \mathbb{N}$ the number of ARs;
- $\theta_{i,j} \in \mathbb{N}$ the number of opportunities of satellite i w.r.t. the AR j;
- $\sigma_i \in \mathbb{N}$ the number of available downlink opportunities of satellite i;
- $t_{i,j}^{k} \in \mathbb{R}$ the acquisition time of the DTO of the AR j from satellite i at the opportunity k;
- $s_{i,j}^{r} \in \mathbb{R}$ the acquisition time of the DLO of the AR j from satellite i at the opportunity r;

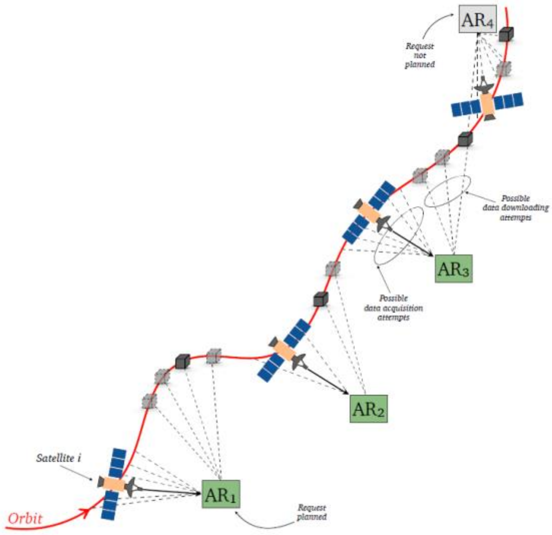


Fig 4 Graphical representation of the mission planning problem. Each satellite "i" has several opportunities to acquire requested scene (AR) and then download them because of memory issues. Mission planning deals with the optimal scheduling of these data acquisition requests

- $\alpha, \beta, \gamma \in \mathbb{R}$ weights associated with the problem.

The goal in this scenario is to minimize $F(\vec{x},\vec{y})$ subject to the following constraints:

- Each target acquisition scheduled once:

$\sum_{i=1}^{n} \sum_{k=1}^{\theta_{i,j}} x_{i,j}^{k} - 1 = 0 \quad \forall j$

- Each target download scheduled once:
  $\sum_{i=1}^{n} \sum_{r=1}^{\sigma_i} y_{i,j}^{r} - 1 = 0 \quad \forall j$

- Mutual exclusion of DTO and DLO
  $$\sum_{k=1}^{\theta_{i,j}} x_{i,j}^{k} - \sum_{r=1}^{\sigma_i} y_{i,j}^{r} = 0 \quad \forall (i,j)$$

- Preparation time vs successive DTOs
  $x_{i,s}^{k} p_{i,s}^{k} - \left| x_{i,s}^{k} t_{i,s}^{k} - x_{i,j}^{k'} t_{i,j}^{k'} \right| \leq 0 \quad \forall (i,j,s,k,k')$

- Preparation time vs successive DLOs
  $y_{i,g}^{r} d_{i,g}^{r} - \left| y_{i,g}^{r} s_{i,g}^{r} - y_{i,j}^{r'} s_{i,j}^{r'} \right| \leq 0 \quad \forall (i,j,g,r,r')$

- Available Memory on board
  $\sum_{j=1}^{m} \left(\sum_{k=1}^{k'} x_{i,j}^{k} - \sum_{r=1}^{r'} y_{i,j}^{r} \right) q_{i,j} - q^{M} \leq 0$

- Target acquisition precede download
  $\sum_{k=1}^{\theta_{i,j}} x_{i,j}^{k} t_{i,j}^{k} - \sum_{r=1}^{\sigma_i} y_{i,j}^{r} s_{i,j}^{r} \leq 0 \quad \forall (i,j) \, \forall (k', r') : t_{i,j}^{k'} \leq s_{i,j}^{r'}$

where other parameters are introduced:

- $p_{i,j}^{k} \in \mathbb{R}$ the preparation time to gain the DTO of the AR j from satellite i at the opportunity k;
- $d_{i,j}^{r} \in \mathbb{R}$ the preparation time to perform the DLO of the AR j from satellite i at the opportunity r;
- $q_{i,j} \in \mathbb{R}$ the needed memory to gain the AR j from satellite i;
- $q^{M} \in \mathbb{R}$ the total memory available on satellite i.

Impact for EO: medium-high. An optimal scheduling could allow for both more acquisitions and time saving. This could enhance early warning systems for time critical events like search and rescue tasks. Not only, it could bring additional revenue by allowing to serve more users at the same time. The increasing trend in larger constellations of smaller satellites (N>>1) is making this problem even more impacting, especially in the case of mission time horizons greater than 24 or 48 hours.

Mission step: data acquisition \ mission analysis

Problem sizing: given the above mathematical description, the number of decision variables to be determined is $N_{var} = \sum_{i=1}^{n}\left(\sum_{j=1}^{m}\theta_{i,j} + \sigma_i\right)$. Since each variable is binary (acquire or not acquire), the mission planning involves searching an optimal solution within $2^{N_{var}}$ possible configurations of DTOs and DLOs. The typical problem size to be managed considering all the constraints above is $N_{var} \sim 10^6 - 10^9$ as current mission planning problems involve constellations with $n \sim 10^2$, $m \sim 10^3$ and $\theta_{i,j} \sim \sigma_i \sim 10$ (depending on the specific problem). Current systems find probabilistic solution in few seconds. See section 5.2.4 for an example of a problem instance.

Bottlenecks: for the single satellite the problem is completely solved but for large constellations the configuration space is too large, so only probabilistic solutions exist. The growing trend of even larger constellations of small satellites imply the need for an optimal solution even with N>>1. Solving the scheduling problem for a satellite constellation becomes a huge computational problem. Adopting meta-heuristic algorithms or based on AI approaches can certainly lead to solutions, but the value of the global optimum is not known.

Classical solution: both deterministic and metaheuristic algorithms (mainly genetic algorithms and simulated annealing)

Potential quantum speedup: unknown. We believe that quantum properties (like superposition) could help in exploring much more configurations in a lower time. Existing solutions have not proven a quantum advantage even for a simplified problem version on current quantum hardware, but it will be interesting to see what happens with the advent of new systems and so with more qubits. A possible mapping of the binary variables into qubits represents an interesting strategy to investigate in order to decrease N_{var}. Finding the exact solution or at least the global optimum would require enormous computation time using conventional HW. In this sense, an exact solution computed by means of a quantum solver would allow a proper tuning of classical (meta-heuristic or AI-based) algorithms.

Existing quantum solutions: yes (this problem can be mapped as a QUBO and then solved on a quantum annealer).

Level of quantum maturity within 15 years: medium. Even if quantum advantage has not been found on a small-scale problem benchmarked against classical solutions, more qubits and new architecture could speed up the quantum solution within the next 15 years.

Bibliographic references: RD-1, RD-2

4.2.3.2 Scenario n°3.2: TASF formulation (Optical Agile Satellites Mission Planning)

Problem's description: The increasing number of satellite systems deployed or under deployment, multiplies the acquisition opportunities, as a given area of interest can often be revisited, as well as the combinatorial of the associated mission planning problem. The optical mission planning problem deals with the optimal scheduling of satellite observations for a given list of user requests. Each "Image Acquisition Request" (IAR) can have several opportunity windows (Data Take Opportunity or DTO) over one or several satellites. Moreover, the satellite agility allows to start the acquisition anywhere inside the DTO. Hence, to correctly exploit the increase of acquisition capacities, it is necessary that the mission planning algorithms increase their performances accordingly. This is true as much from the capability to optimally use the satellite agility and the on-board resources point of view as from the computational speed point of view. Finally, the mission planning algorithm must be flexible and reactive to be able to deal with new perturbations (like meteo forecasting) and last time deposit user requests.

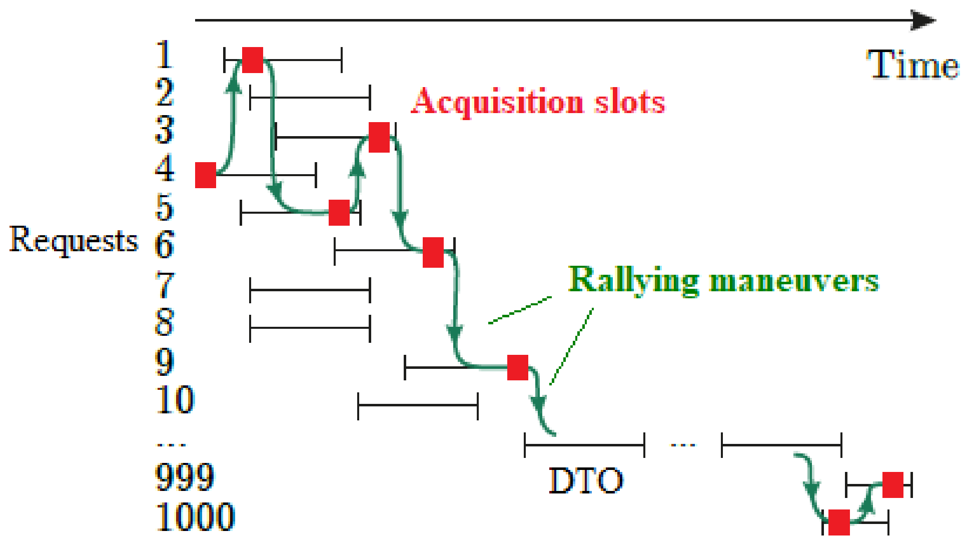


Fig 5 Satellite Acquisition Workplan

Impact for EO: medium-high. As complex/numerous/heterogeneous satellite systems can no longer be operate manually by operators, an optimal scheduling could allow to achieve optimal usage of satellite' capacities. This could bring additional revenue by exploiting the maximum satellite capability and save operator human resources.

Mission step: mission design and data acquisition

Problem sizing: satellite mission planning can be a computationally hard problem to solve; in large-scale missions, the size of the problem requires a prohibitive amount of computational resources. Finding an efficient plan requires the optimization of movement and the re-ordering of tasks to maximize the number of total completed tasks. For example, for an area of interest including 100 elementary zones (called meshes) to be acquired by a satellite, these meshes are in competition with each other because, when the satellite passes over the zone, it has the capacity to acquire any of the meshes. If we consider that the satellite agility allows the acquisition of 10 to 15 images per pass over the area of interest, the number of possible combinations is about 10^{169}. If now we consider the real number of acquisition requests in the mission catalog for one or two days (planning horizon) and constellations of 10 up to 200 satellites, when searching for a global optimum, the problem jumps to 10^{1700} up to 10^{34000} combinations to be explored. Current non-complete search mission planning algorithms with meta-heuristics, cannot handle such big constellations with a satisfying guaranty of having a "good" solution for the exhibited mission plan. However, a good indicator of the mission plan quality could be the assessment of the usage ratio of each satellite of the constellation.

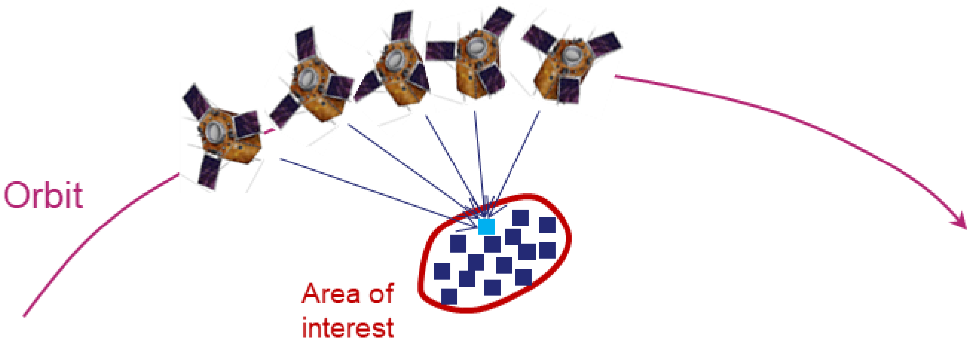


Fig 6 Different possibilities inside the DTO to start the acquisition.

Bottlenecks: For huge observation satellite constellations and for mission planning horizons going from some days (in operational mission centers) up to one year or more (for mission simulators), the use of classical optimization algorithms with meta-heuristic cannot be envisaged, even if the optimum cannot be guaranteed due to the incompleteness of the state-of-the-art algorithms. Optimization of satellite mission plan for such big constellations of agile satellites needs implementation of new complete optimization algorithms.

Classical solution: Typically, the mission-planning algorithm requires the re-ordering of requests to maximize the number of completed acquisitions while considering their level of priority. This combinatorial problem requires an exponentially growing number of configurations to be studied as the number of requests and satellites increases. Current methods are mostly non-complete search algorithms with meta-heuristics. However, they do not offer a satisfying guaranty of having a "good" solution for large constellations of tens/hundreds of satellites.

Potential quantum speedup: unknown precisely. Recent explorations performed on simulated quantum computers, shown better mission plan on a restricted scenario (only one type of request priority considered) compared to state-of-the-art (SotA) algorithm. We experienced, even if it is a preliminary result, that quantum properties (like superposition) can help in exploring much more configurations in a lower time. Up to now, existing explorations have not proven a significant quantum advantage even for a simplified problem version on current quantum hardware, but it will be interesting to see what happens with the advent of new systems and so with more qubits. It is very important to notice that there are two ways of expected improvement on this use case:

- a speed up to get a solution at least as good as SotA one,
- a better solution than SotA one, but in a time duration at most in the order of magnitude of the SotA one.

Existing quantum solutions: yes (some tentative with clustering, and mapping of the problem as a QUBO or as a Reinforcement Learning model). Usage of quantum annealer has demonstrated major difficulties to address the use case [RD-1]

Level of quantum maturity within 15 years: medium. Even if quantum advantage has not been demonstrated on a small-scale problem benchmarked against classical solutions, more qubits and new architectures could speed up the quantum solution within the next 15 years.

Bibliographic references: RD-1, RD-21

4.2.4 Scenario n°4: Multiple-view Geometry on optical images (TASF)

Problem's description: from a set of N optical images with P = <rows x cols> pixels, retrieve relative pose, terrain elevation and potential changes. These can be estimated minimizing a single functional with the following parameters:

- Relative rigid pose transformation: (N-1) x 6 degrees of freedom,
- Terrain reconstruction: P degrees of freedom,
- Change detection binary mask: (N-1) x P degrees of freedom.

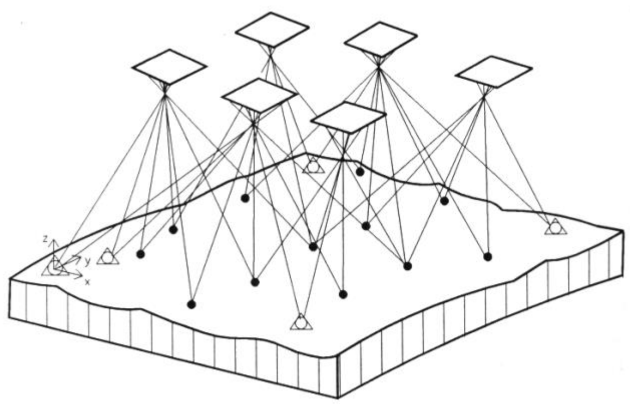


Fig 7 Example of multiple (6) views from a scene

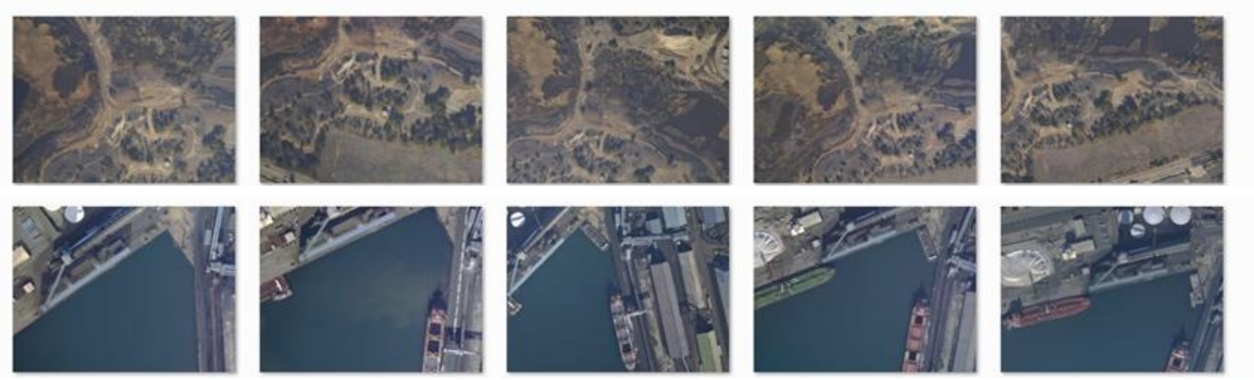


Fig 8 Sets of 5 images used for the use-case

Impact on EO: “medium”: ability to minimize functionals with very high number of degrees of freedom in a limited time might allow more accurate approach for terrain reconstruction and reduce constraints on satellite platform localization and attitude precision.

Mission step: data processing

Problem Sizing: One set of images of the Test Dataset contains 5 images of 3000 x 2000 pixels on 3 RGB channels. On a VHR optical satellite, images are 30000 x 30000 pixels on 4 channels.

Bottlenecks: this problem can’t be solved as one large optimization with current computing techniques, as exploring the whole solution space is an exponential computational problem, the size depending on the required precision. Heuristics and problem decomposition needs to be applied for this photogrammetry use-case.

Classical solution: The classical solution uses photogrammetry methods and library such as OpenCV for:

- Keypoint detection and description with SIFT method: 2000 keypoints per image
- Robust Keypoint Matches between corresponding images
- Pose estimation
- Image Warping
- Terrain estimation

This prototype takes 4.6s per set on a 3GHz CPUcore.

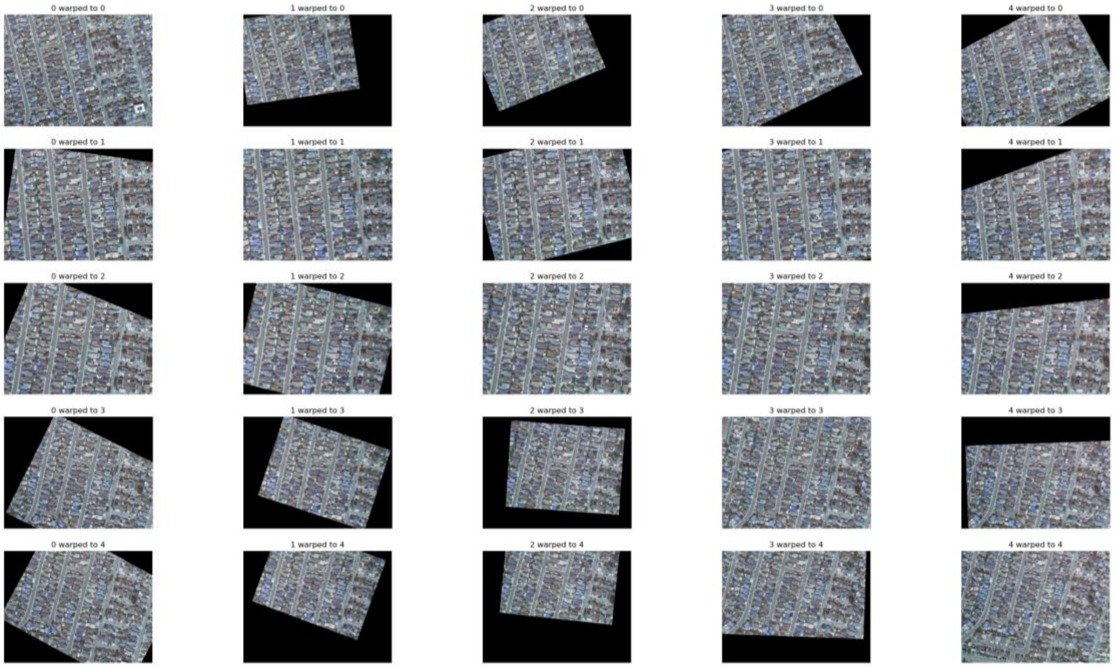


Fig 9 example of images warped in the geometry of other images of the set

Existing quantum solutions: yes [RD-22]

Potential quantum speedup: unknown. It's difficult to extrapolate performances on larger scales starting from small size implementations. The idea here is to understand if quantum circuits can improve the expressivity of the model, there is no proof that the solution would be of better quality than classical ones (there is a tradeoff between performances and resources).

Level of quantum maturity within 15 years: "high": it's very likely that the quantum solution could target the full size problem (or working as a dedicated QPU) because the only issue is scalability of current devices.

Bibliographic references: RD-22

4.2.5 Scenario n° 5: SAR Digital Beam Forming (TASI)

Problem's description: Traditional SAR systems have a tradeoff between swath width and resolution: to overcome this tradeoff multi-channel SAR systems with N independent receiving channels have been introduced. Digital beamforming (DBF) techniques have been developed to process these independent acquisitions by a joint spatiotemporal processing of the recorded sub-aperture signals. DBF acts directly on the received digital signals at the ADCs' output (Fig 10). DBF makes a linear combination of the output signals with weights to steer the received beam toward the target and cancel interferences. Here we will refer to the Displaced Phase Center (DPC) techniques for DBF on a single satellite platform.

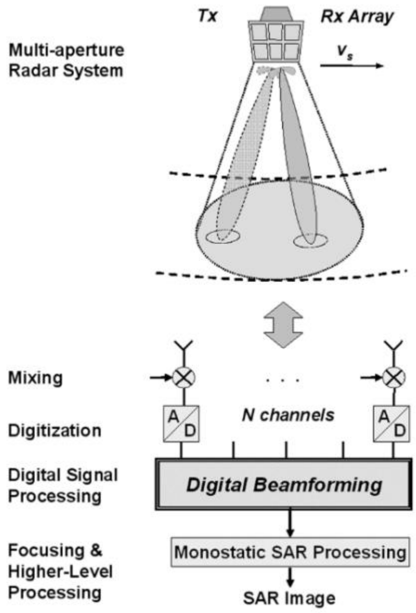


Fig 10 Multi-aperture system with the formation of several beams together with the block diagram of the DBF on the receive principle [RD-25]

Impact on EO: medium. The current trend is to increase the number of independent channels on SAR systems, so it could be interesting to evaluate if an on-board QC solution could give some kind of speedup.

Mission step: data acquisition

Problem sizing: currently, only few systems exist equipped with on-board DBF as described in this section (mainly due to hardware limitations as described later); not only, these systems have a limited number of independent channels: for example, TerraSAR-X satellite has two independent RX channels [RD-30]. Other solutions with more channels exist, but in this case only a part of the beamforming is done on-board. For example, future ESA mission ROSE-L will be equipped with on-board beamforming capabilities in the elevation direction (SCan-On-REceive - SCORE - method) while azimuth beamforming is done on ground (the independently acquired signals are digitized on-board and then sent on ground to be processed; this technique is called MAPS: Multi-Azimuth-Phase-Center). ROSE-L will use 4 digital channels for the on-board real-time elevation beamforming and 5 digital channels for the ground beamforming [RD-31].

Bottlenecks: at the moment, the current maximum number of apertures (TX\RX modules) put onboard for DBF is small, so the processing is well-handled by classical algorithms. Here, the main bottleneck is given by the power consumption and mass of the processing payload (ADC and processor). The computational complexity of this algorithm is the same required to solve a system of N linear equations, i.e., $O(N^3)$; this is needed to unambiguously recover the formerly aliased azimuth spectrum.

Classical solution: The Multi-Aperture Reconstruction Algorithm is founded on a generalization of the sampling theorem according to which a band-limited signal U (monostatic SAR signal) is uniquely determined in terms of the responses of N linear systems (the N receiving channels) with input U, sampled at 1/Nth of the Nyquist frequency. The reconstruction consists essentially of N linear filters $P_i(f)$ which are individually applied to the subsampled signals of the receiver channels and then combined coherently (Fig 11). The reconstruction filters can be derived from the inversion of a matrix H(f) consisting of the N transfer functions $H_i(f)$.

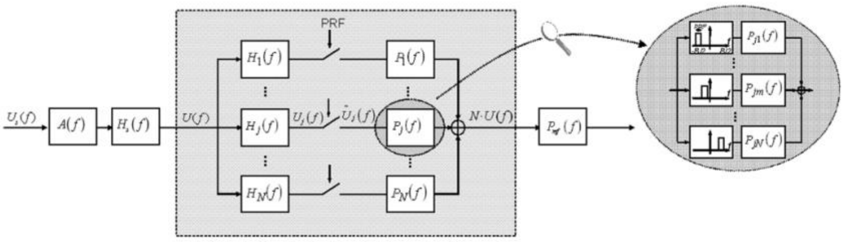


Fig 11 Multi-aperture reconstruction algorithm in case of three channels [RD-25]

Existing quantum solutions: no

Potential quantum speedup: unknown. It will be interesting to understand if QC algorithm for linear equation systems could give a speedup (e.g. HHl algorithm). However, It will be interesting to understand if QC hardware could give a speedup regarding power consumption and/or mass (for example photonic QC). Furthermore, if the number of independent channels N will grow, QC could became important for efficiently optimizing weights [RD-24]

Level of quantum maturity in the next 15 years: low. Not clear if QC algorithms are really needed to make more this problem more efficient. Regarding mass and power consumption, space qualified quantum hardware probably will not be available within 15 years.

Bibliographic references: RD-24, RD-25, RD-30, RD-31

4.2.6 Scenario n° 6: InSAR Phase Unwrapping (TASI)

Problem's description: The phase unwrapping problem is crucial in SAR interferometry (InSAR). SAR interferometry is a powerful remote sensing techniques that enables highly accurate measurement of important geophysical parameters (e.g. surface topography, subsidence, ground deformations) by comparing the same scene from two different point of views. It can be divided into "across-track interferometry" (different views of the same scene taken at the same time) or "along-track interferometry" (time delay between two or more view of the same scene, keeping fixed geometry). In both cases it's important to align the raw images by pixel and extract the information on the "phase difference" between each pixel pair (remember that SAR raw data are complex values that contain information about both amplitude and phase of the back-scattered echo signals): in this way it's possible to measure small path length differences up to millimeter accuracy. A fundamental challenge is the "phase unwrapping": recovering unambiguous phase values from a two-dimensional array of phase values known only modulo 2π rad. Algorithms that compute the phase of a signal often only output phases between –π and π, so unwrap algorithms add appropriate multiples of 2π to each phase input to restore original phase values.

$$\phi_i = \varphi_i + 2\pi k_i$$

$$E = \sum_{(s,t)\in A} W_{st}(k_t - k_s - a_{st})^2 + \sum_{s\,\in A} \omega_s (k_s - a_s)^2$$

Here φ_i is the "wrapped" phase (measured) and ϕ_i the "unwrapped" phase.The goal of phase unrapping algorithms is to find the best array ok k (one k value for each pixel in the InSAR image) that minimizes the energy cost function E (here indices s,t run over the entire image A, W_{st} are weights defining the neighborhood structure, a_s are constant terms and ω_s are weights that enforce E to prefer small values of k).

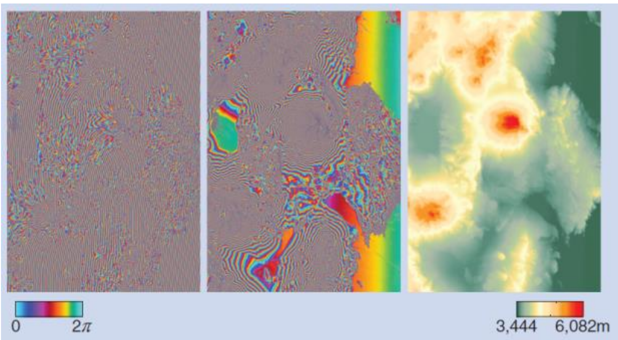


Fig 12 SAR interferogram of the Atacama desert (Chile). Starting from left: complex interferogram after the alignment of two SAR images. Center: removal of the flat Earth contribution. Right: the unwrapped phase has been converted into height values [RD-18]

Impact on EO: low. SAR system experts judge this problem yet solved by classical algorithms (processing times are yet very short and results quite good for practical applications). For these reasons quantum speedup could be useful but not priority at the moment.

Mission step: data processing

Problem sizing: InSAR images quite large, often exceeding 20 k × 30 k, or 600 M, pixels.

Bottlenecks: SAR image too large, too much time required. Also, the MCF solution is rather memory intensive. The network topology is critical for MCF.

Classical solutions: formulate the problem as a minimum cost flow (MCF) problem then using the sequential tree weighted message passing (TRWS) algorithm as solver. Time and space complexity high, but robust result.

Existing quantum solutions: yes. QUBO problem on a quantum annealer.

Potential quantum speedup: unknown. At the moment with current devices, when tested on a quantum annealer it shows results similar to classical benchmarks (TRWS)

Level of quantum maturity in the next 15 years: Medium. The quality of the solution depends not only on the number of available qubits but also on the embedding on a quantum annealer. In the simplest problem where each pixel label would require one qubit, a 600-M-qubit quantum annealer would be required; such a machine is not currently available.

Bibliographic references: RD-18, RD-23

5 Use Case Definition and Motivations

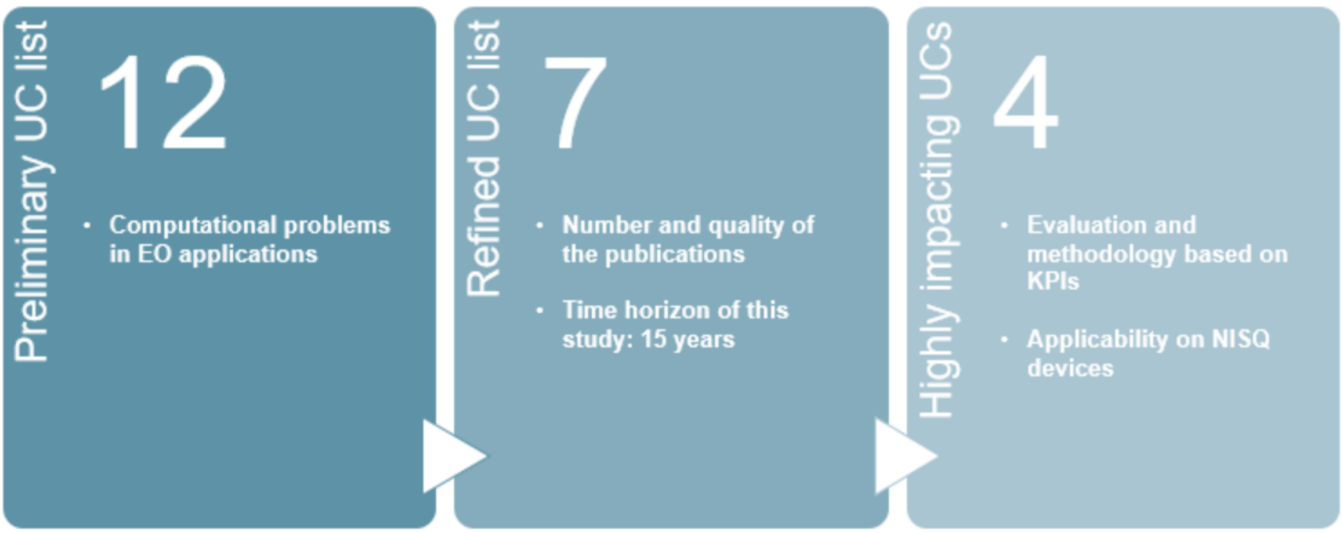
This chapter contains the shortlist of the selected scenarios that will become the Use Cases for the QC4EO project. These UCs are the core of QC4EO and will be analyzed in the following WPs up to the roadmap definition. For each selected UC, the next sections report the following information:

- **Motivation**: why the specific scenario has been selected for this shortlist.
- **Quantum algorithm**: the quantum algorithm that will be investigated within the UC.
- **Classical vs Quantum Architecture**: classical workflow logic (or flow diagram of the algorithm) compared with the correspondent quantum version; this section must convey the message of which part of the classical architecture the QC could come in, possibly including hybrid architectures.
- **Problem instance**: a complete instance of the variables needed by the problem, based on a real scenario; this information will be useful for machine sizing (WP 2).

From this point on, the numbering of the use cases will not be strictly related to their impact but will follow the one used in the following project's deliverables.

5.1 From scenarios to UCs

In the following figure, the overall decision process that reduced the starting 12 scenarios to the final 4 use cases is illustrated:



In this last selection, the main drivers have been:

- The KPIs of each scenario (mainly the expected potential impact on EO)
- The applicability on NISQ devices

5.2 Use case n°1: Mission Planning for EO Acquisitions (TASI, TASF, INFN)

5.2.1 Motivation

Mission planning lies at the heart of EO, being the tool that optimizes and schedules the acquisition requests coming from end-users. Current approaches to solve this problem are based on both determinist and metaheuristic algorithms that can generate optimal solutions for current constellations of few satellites. However, there is an increasing trend to deploy large constellations of small satellites (N > 100), making the optimal solution of the mission planning problem increasingly difficult to find even for small planning time horizons (few days), both in terms of time and quality. Furthermore, these large new constellations are even more complex due to the Inter-Satellite Link (ISL) so the planning algorithm must take into account the possibility for the satellites to communicate between them and so updating their on-board activity list without direct ground-space communication. It is straightforward that this solution dramatically decreases the system response time but, on the other side, add more complexity to the mission planning problem.

On general, the goal of the mission planning algorithm is to:

- minimize the response time of the system, i.e. the latency between the submission of a service request by the user and the download of the product.
- Uniform distribution of tasks among the satellites constituting the constellation, i.e. load-balancing.
- Maximization of the image quality, depending on the user need.

Is not a case that both TASI and TASF believes it is urgent to study how quantum computing could help in this problem, evaluating the potential quantum speedup not only in terms of time required for the calculation but also in terms of quality of the solution.

5.2.2 Quantum algorithm

Three possible approaches for applying QC to mission planning will be investigating:

- **Full quantum** (TASI - INFN): mapping the classical problem on a QUBO problem and solve it with a quantum annealer.
- **Hybrid** (TASF): use of a Quantum Neural Network (QNN) as a policy model within a classical reinforcement learning (RL) framework.
- **Hybrid** (FZJ): QAOA (inherently hybrid) on a NISQ device.

5.2.3 Classical vs Quantum Architecture

5.2.3.1 Full quantum formulation as a QUBO problem (TASI - INFN)

TASI is currently tackling the problem of mission planning with both deterministic and metaheuristic algorithms, like for example genetic algorithms. On general, classical mission planning architecture is reported in the following figure:

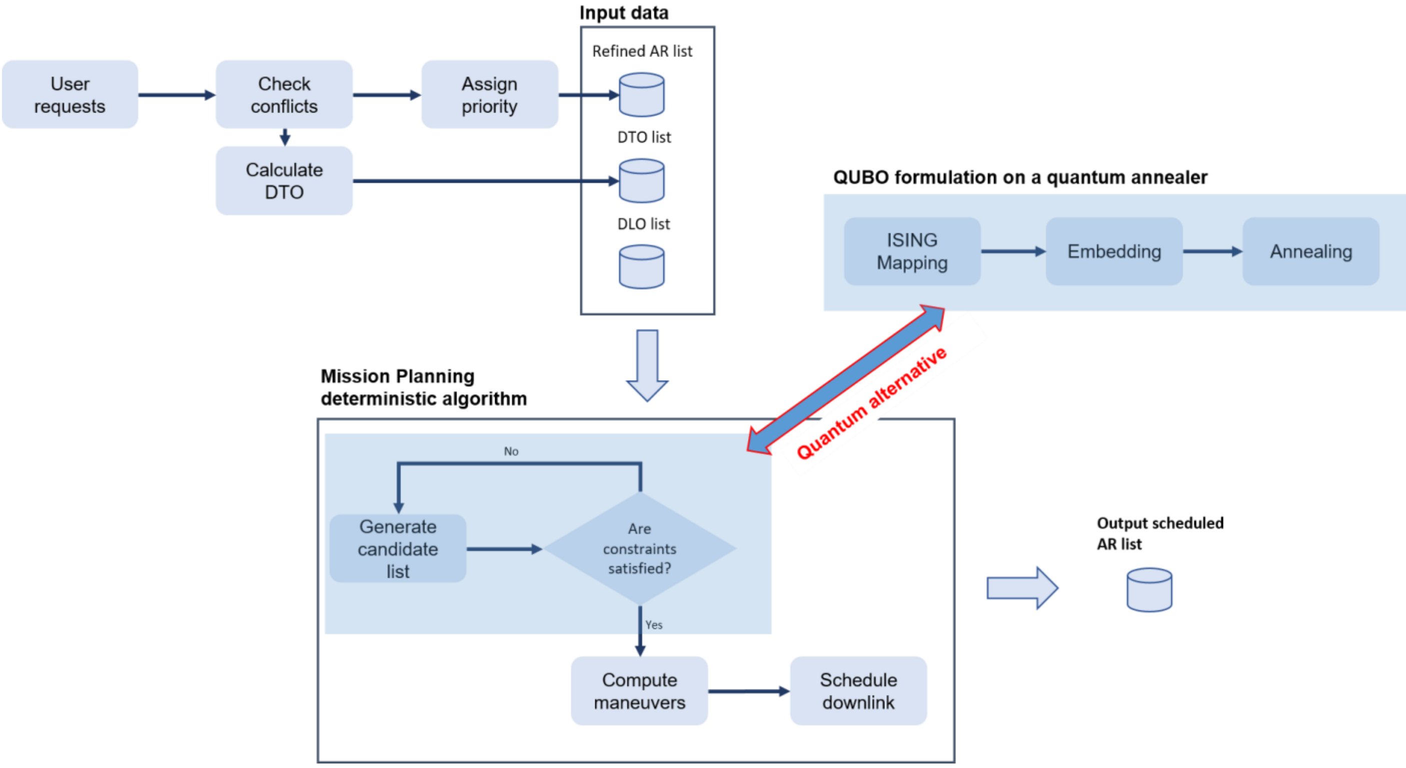


Fig 13 Logic of the mission planning algorithm highlighting where QC will come in. It is envisioned as a separated block to be run on a dedicated QPU that will take the same input of the classical deterministic\metaheuristic algorithm and will return the optimized list of ARs for each satellite.

End users plan their acquisition requests, and a preliminary check is performed to eliminate possible conflicts; then a series of hand-crafted rules assign a priority to each request. This list of refined ARs is the input of both the classical and quantum mission planning algorithms, together with the list of data take opportunities (DTO) and data downlink opportunities (DLO).

The current classical approach tries to generate candidate solutions that satisfy all the constraints: for small constellations of few satellites state-of-the-art algorithms can find the global optimum solution in a short time. But for larger constellations these algorithms cannot reach the global optimum, giving only approximate solutions.

TASI is currently investigating a full QC solution that maps the classical problem onto a QUBO problem. The QUBO problem can be embedded on a quantum hardware to be then solved by quantum annealing. The output of the algorithm, both quantum and classical, is a vector of binary variables, that naturally satisfy all the constraints, specifying when a target must be acquired and when stored data must be downloaded. These variables, together with maneuverers calculation, constitute the mission plan for that constellation.

Current main limitations to this QC approach are the available number of qubits and the embedding of the variables on the quantum hardware.

Important KPIs for benchmarking are:

- Average computation time and related HW usage;
- Distance from global optimum;

- Distribution of acquisition requests on the different satellites composing the constellation (load-balancing);
- Average information age (and/or system response time) on high priority requests;
- Average image quality
- Scalability of these indicators with respect to both the satellite number and the number of ARs.

5.2.3.2 Hybrid formulation as a QNN in a RL framework (TASF)

As the number of satellites under deployment increases, the number of opportunities to generate images of selected areas of interest significantly increases. The optical mission-planning problem consists in obtaining an optical scheduling of the satellite observation for a given list of acquisition requests (AR). This becomes even more challenging as these areas of interest may be visited multiple times and the agility of the satellites allows starting the acquisition anywhere inside the data take opportunity (DTO) of the requests.

To obtain a solution that fulfils these challenges and constraints, it is important to have an optimal performance of on-board resources and optimal computational complexity. A high computational speed of the mission-planning algorithm would allow for more flexibility and fast adaptability to perturbations.

Typically, the mission-planning algorithm requires the re-ordering of requests to maximize the number of completed acquisitions while considering their level of priority. This combinatorial problem requires an exponentially growing number of configurations to be studied as the number of requests and satellites increases. Current methods are mostly non-complete search algorithms with meta-heuristics. However, they do not offer a satisfying guaranty of having a “good” solution for large constellations of tens/hundreds of satellites.

Previous work by TASF alongside Terra Quantum has enabled the comparison of multiple quantum approaches using clustering, optimization, and machine learning methods in a hybrid classical-quantum way with classical algorithms. It is shown that a classical pre-processing step to cluster the requests and data (by bunching or K-means) enables a simplification of the problem and a more efficient search for an optimal solution. A hybrid optimization approach is motivated by the fact that when combined to quantum computing (QA or QAOA), a QUBO formulation (NP-hard problem), can offer up to a quadratic speedup. An *integer optimization* (branch-and-cut) algorithm using the Gurobi solver is shown to achieve a much higher completion rate of high-priority requests than a simple classical greedy algorithm (98.1% versus 63.6%). This result suggests that adopting an optimization approach using quantum computing may lead to a potential speedup, not to mention that a hybrid solution is well suited to both NISQ and FTQC era.

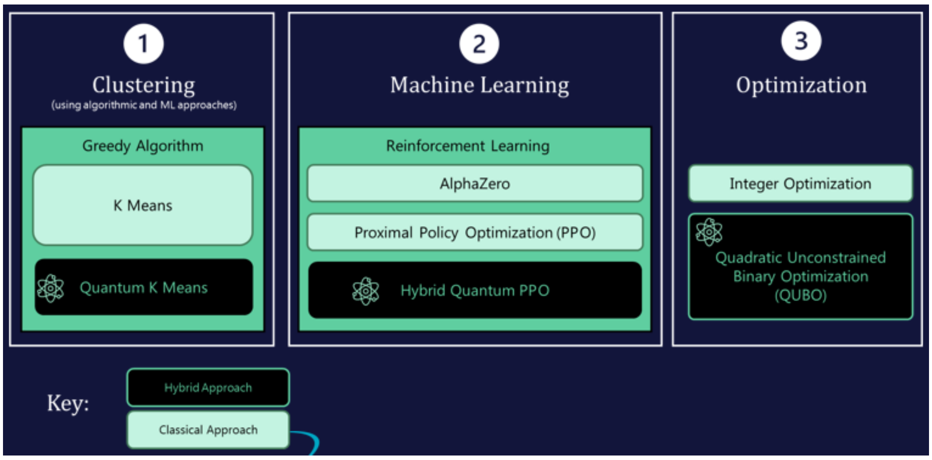


Fig 14 Multiple quantum approaches using clustering, optimization and machine learning methods

Additionally, two hybrid quantum-classical machine learning algorithms have been tested. The first one is a hybrid Proximal Policy Optimization (PPO) algorithm and the second one a hybrid AlphaZero algorithm. Both make use of a 4-qubit parameterized quantum circuit (PQC) composed of a first layer of controlled-X rotations and CNOT gates to entangle the qubits, followed by a series of eight layers of data encoding blocks that encode 32 features overall. In the hybrid PPO algorithm, a classical neural network processes a large set of features that represent the data to reduce the number of features to be encoded in the quantum neural network.

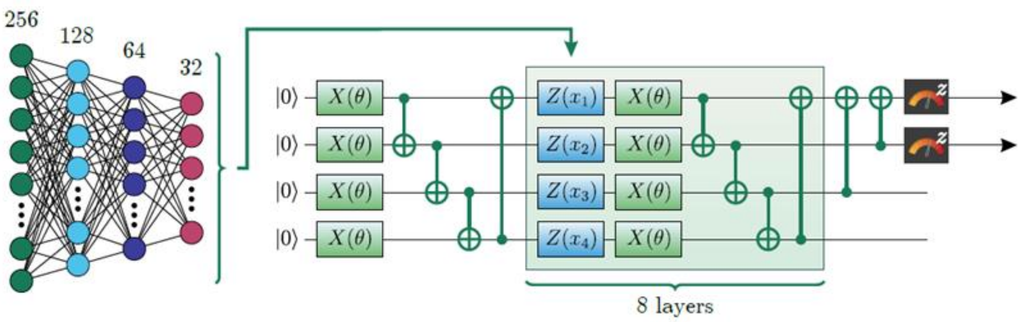


Fig 15 Quantum-hybrid reinforcement learning model. A quantum circuit (left) is added to the beginning of the MLP Agent in the RL model (right) to incorporate quantum computation into the neural network

This algorithm demonstrates that the reward for the Reinforcement Learning agent is much larger than that of the classical greedy algorithm in a rather small number of steps. Based on this result, one could expect to see an improvement either in the quality of the solution or in the speed to optimal solution by using quantum computing. The hybrid AlphaZero algorithm makes use of a Monte Carlo Tree Search in conjunction with the previously described PQC as well as a single neuron fully connected network run in parallel to the quantum circuit. Overall, this algorithm achieves a high completion rate when compared to any other algorithm studied in the most complex configuration (2 satellites and 2000 requests). It is therefore possible to obtain an improvement in terms of quality of the solution over classical algorithms by using a hybrid quantum-classical machine learning approach.

5.2.4 Example of a problem instance

5.2.4.1 TASI radar constellation

In order to help the machine sizing for the mission planning problem as modeled by TASI and INFN, the following data can be helpful to have an idea of the number of variables and complexity required for a medium-size modern radar constellation for EO (all data consider a planning mission horizon of 24h):

- **Number of satellites**: ~30
- **Average revisit time (constellation)**: hourly
- **Average raw data size** (given a certain acquisition mode) [Gb]: ~40
- **On-board memory** [Gb]: ~1000
- **Average pointing time** (time to rotate from +45° to -45° with respect the zenith of the satellite) [s]: 10÷60
- **Average number of acquisition request per day per satellite** (estimated): 200
- **Maximum number of AR to be scheduled (constellation):** 50000
- **Average number of DTO per satellite** [s]: 2÷50 (strongly dependent on orbital parameters of the specific constellation)
- **Average number of times the satellite pass over a Ground Station** (Data Downlink Opportunities): 10÷100 (strongly dependent on orbital parameters of the specific constellation and ground station locations)
- **Average acquisition time** (mean access duration) [m]: 2÷15
- **Downlink data rate** [Mbit\s]: ~500

5.2.4.2 TASF optical constellation

A classical instance of the optical mission planning problem is:

- 10 to 100 satellites in constellation
- 10.000 to 100.000 acquisition requests to be planned on a 24-hour horizon period with different acquisition modes, among which:
  - Monoscopic
  - Bi or tri-stereo
  - Mozaic…

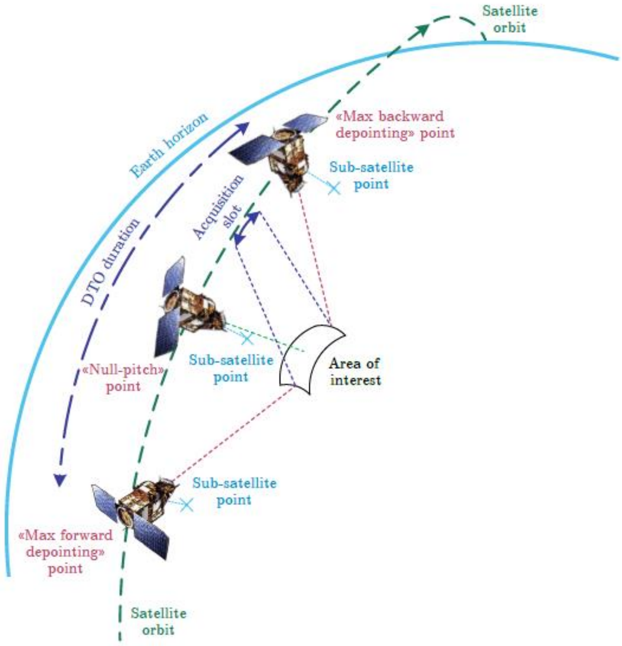


Fig 16 The trajectory of a satellite orbiting on the Earth's terminator and across a DTO window. At the first and third positions on the orbital line, the satellite is at the ends of the request's DTO window, as its depointing angle is maximized at 45°. At its second position, it is at the apex point, directly above the request location.

This figure demonstrates the satellite movements during acquisition, as well as the data that has to be tracked during the capture, such as the angles of acquisition, the points at which the DTO begins and ends, and the median coordinates.

5.3 Use case n°2: Multiple-view geometry on optical images (TASF)

5.3.1 Motivation

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 DTO window or multiple passes. An important task is to analyse 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 (typically described by SIFT descriptors), then by matching those that are common to multiple images. Finally, a projection that aligns the coordinate systems of all images must be identified, followed by a transformation to align all images in a single plane (typically Direct Linear Transformation or eight-point algorithm).

From there, image classification methods or other techniques allow for further study of the area of interest such as the identification of moving objects.

5.3.2 Quantum algorithm

The possible approaches for applying QC to bundle adjustment are:

- **Full quantum**: mapping the classical problem on a QUBO problem and solve it with an annealer
- **Hybrid**: use of hybrid quantum-classical algorithm for image matching

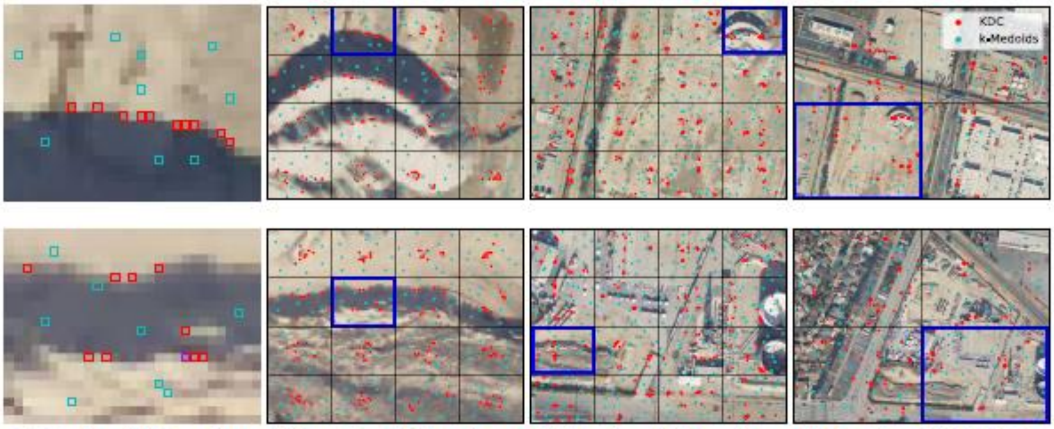
5.3.3 Classical vs quantum architecture

The classical solution uses photogrammetry methods and library such as OpenCV for:

- Keypoint detection and description with SIFT method: 2000 keypoints per image
- Robust keypoint matches between corresponding images
- Pose estimation
- Image warping
- Terrain estimation

In previous works, TAS-F in cooperation with Fraunhofer Institute, decided to perform keypoint extraction and feature matching in a quantum manner while the final steps, i.e., the image transformations, are classically performed since the transformation is inherently continuous and therefore not well suited to quantum computing.

The quantum keypoint-extraction process is interpreted as a clustering problem and two algorithms are proposed: quantum k-medoids clustering and quantum kernel density clustering. In both cases, the classical problem is formulated as a QUBO. The former consists in selecting k distinct objects located in the centre of the image. The latter consists in finding optimal cluster centroids using a kernel feature map.



(a) Extraction of 10 keypoints on a single image patch. (b) Extraction of 10 keypoints on every image patch. (c) Extraction of 20 keypoints on 4 × 4 grid. (d) Extraction of 45 (final) key-points on 4 × 4 grid.

Fig 17 Extraction of key points from several kinds of grids

Typically, a Gaussian distribution represents each point. However, TAS-F and Fraunhofer Institute consider a **quantum kernel** whose matrix is computed via a quantum circuit. It is observed that the extracted keypoints are generally equally distributed within the image for the k-medoids clustering, whereas they are located on edges of objects contained in the images for the kernel density clustering method (when a sufficient number of pixels represents these edges).

5.3.4 Example of a problem instance

One set of images of the Test Dataset contains 5 images of 3000 x 2000 pixels on 3 RGB channels. On a VHR optical satellite, images are 30000 x 30000 pixels on 4 channels.

The final image is described by 1000-2000 keypoints in total and needs to be splitted in smaller scale sub-images (patches, see Fig 17).**T**his problem can't be solved as one large optimization with current computing techniques. Heuristics and problem decomposition needs to be applied for this photogrammetry use-case.

5.4 Use case n°3: Optical Satellite Data Analysis (FZJ)

5.4.1 Motivation

The analysis of optical satellite data is pivotal for EO, as it plays a fundamental role in classifying and understanding the various facets of our world. A prime example of its importance is evident in land cover classification, a process that categorizes physical materials on the Earth's surface into distinct classes, such as forests, wetlands, urban areas, or agricultural fields. Figure N illustrates a classical classification system. This system can generate classification maps by learning from satellite data, thereby providing an invaluable resource for understanding and managing the Earth's land resources effectively

Fig 18 workflow of a classical classification system

The emphasis here is on model training, a process that is both data and compute-intensive. This processing step is challenged not only by the high computational complexity of the algorithms involved, but also by the increasing availability of labeled training data. Indeed, publicly available land-cover maps (e.g., CORINE land cover map) can be utilized to extract a large number of reliable labeled training samples. This study primarily concentrates on the application of kernel methods, a core element of machine learning frameworks. Perceived as a dual-stage methodology, kernel methods begin by transforming data from its initial input form into a high-dimensional kernel feature space using a nonlinear function. Following this, a linear issue is resolved in the newly transformed space. This unique approach seamlessly amalgamates statistical and geometric interpretations of learning algorithms in the kernel space, an area non-linearly tied to the input space, ensuring the derivation of singular solutions.

5.4.2 Quantum algorithm

The Quantum Kernel Estimation (QKE) algorithm aims at constructing a kernel function that is calculated by the usage of a PQC to ''encode'' the feature vectors in a corresponding quantum state. The obtained kernel function is then used to construct the Gram matrix, i.e. the symmetric matrix storing the kernel function evaluation between every data point of the training set, to implement kernel-based ML models such as SVM and GP.

A PQC whose parameter values are data-dependent is used to associate to an input feature vector **x** a corresponding quantum state $|\phi(\mathbf{x})\rangle$ by applying the unitary $\mathcal{U}_{\mathbf{x}}$ to the reference initial state $|0^{\otimes n}\rangle$. In this setting the quantum circuit performing the encoding is also referred to as ''quantum feature map''. The kernel function evaluation between two feature vectors **x** and **y** is obtained by considering the fidelity between the corresponding quantum states $|\langle\phi(\mathbf{x})|\phi(\mathbf{y})\rangle|^2$. The choice of the fidelity between the quantum states as a way to calculate the kernel function ensures that the quantum kernel defined in this way is a symmetric positive semi-definite function, as required by kernel theory [RD-11]. The fidelity between quantum states, however, cannot be directly accessed and thus must be estimated through a sampling procedure. A widely used strategy is to employ the inversion test: by applying the circuit $\mathcal{U}_{\mathbf{y}}^{\dagger}\mathcal{U}_{\mathbf{x}}$ to the initial state $|0^{\otimes n}\rangle$ and then performing a measurement in the computational basis it is possible to obtain an estimation of the quantity $|\langle 0^{\otimes n}|\mathcal{U}_{\mathbf{x}}\mathcal{U}_{\mathbf{y}}^{\dagger}|0^{\otimes n}\rangle|^2 = |\langle\phi(\mathbf{x})|\phi(\mathbf{y})\rangle|^2$, which corresponds to the probability of obtaining the state $|0^{\otimes n}\rangle$ when performing a measurement on the state $\mathcal{U}_{\mathbf{y}}^{\dagger}\mathcal{U}_{\mathbf{x}}|0^{\otimes n}\rangle$ on the computational basis.

The accuracy of the estimation depends on the number of samples used in the sampling procedure. The Kernel matrix obtained in this way, however, might not be positive-definite because of the sampling error and therefore some extra processing on the matrix is needed to obtain a well-defined Gram matrix.

Some implementations of Quantum Kernel algorithms also include parameters of the feature map that can be variationally optimized, such as the works presented in [RD-28] and [RD-29], in which the feature map was optimized with respect to a Kernel Alignment loss function. The optimized kernel is then used in the training phase of a ML kernel algorithm.

5.4.3 Classical vs quantum architecture

The classical and quantum kernel algorithms are both used to construct a Gram matrix that is then used in conjunction with some kernel-based ML algorithms. The difference between the two methods lies in the way that the matrix is obtained: for the quantum version this is done by estimating the fidelity between two quantum states, whereas for the classical kernel this is carried out by evaluating an appropriate kernel function on a classical computer. Therefore, the quantum kernel defined in this way does not describe a new ML algorithm but rather a novel way to estimate the kernel function used in well-known ML algorithms.

5.4.4 Example of a problem instance

This is an example of a problem where a classification map is generated based on a time series of Sentinel-2 data. The specific geographical region covered by the Sentinel-2 product is an orthorectified tile, spanning an area of 100km by 100km. To achieve precise classification results, a time series of Sentinel-2 acquisitions spanning spring, summer, and fall is necessary. This enables the classifier to effectively differentiate between the various land cover classes identified in the provided classification scheme. Sampling the temporal signature of these classes during this period significantly enhances classification accuracy, in comparison to the results garnered using single-date acquisitions. For example, land cover classes such as 'Cropland' and 'Grassland' may present similar spectral behaviors in April due to their comparable vegetation states. Nevertheless, this ambiguity can be resolved by incorporating data from subsequent months. 'Cropland' pixels reveal a phenological trend that does not affect 'Grassland' pixels, mainly because there is no harvesting procedure for the latter. It's important to note that a denser time series of Sentinel-2 images is necessary when handling classes that show high temporal variability throughout the year, such as those experiencing rapid rates of change. Conversely, longer time series of Sentinel-2 images prove beneficial for managing complex classification schemes, like distinguishing between different types of cultivation. Consider the following example of a Sentinel-2 time series, composed of five acquisitions or products. Its total size ranges around 10.68 GiB. For each product, the spectral bands considered are those acquired at 10m and 20m spatial resolution. Bands at 60m resolution are disregarded as they predominantly relate to the atmospheric correction process. Hence, each training set sample includes 10 spectral bands multiplied by 5 dates, equating to a total of 50 features. The number of annotated training samples may be significant when samples are extracted from the CORINE land cover1, given that a single Sentinel-2 tile covers an area of 10,000 square kilometers. The execution time is influenced by the higher-dimensional space that must be considered during training. For example, the computational training complexity of a SVM classifier, considering the use of the RBF kernel, lies between $O(dn^2)$ and $O(dn^3)$), where d is the number of dimensions and n is the training size. The SVM computational prediction complexity is approximately, where d is the relevant dimensions.

[1] CORINE Land Cover: https://land.copernicus.eu/pan-european/corine-land-cover

5.5 Use case n°4: SAR Raw Data Processing (FZJ - TASI)

5.5.1 Motivation

The growing acquisition rate of remote sensing data, including SAR data, would benefit from a computational speedup in data processing. Quantum computing has shown a significant potential in providing a speedup over classical computation in specific cases. QFT has been widely employed in the literature, mostly as a component of bigger quantum circuits. The focus on QFT is motivated by the fact that many SAR image formation algorithms, including the above-mentioned RDA, are based on multiple FFT iterations, and QFT is the direct quantum counterpart of FFT. Since both the feasibility and the possible speedup of a quantum algorithm for SAR image formation are not investigated, this use case turns out to be an interesting research direction.

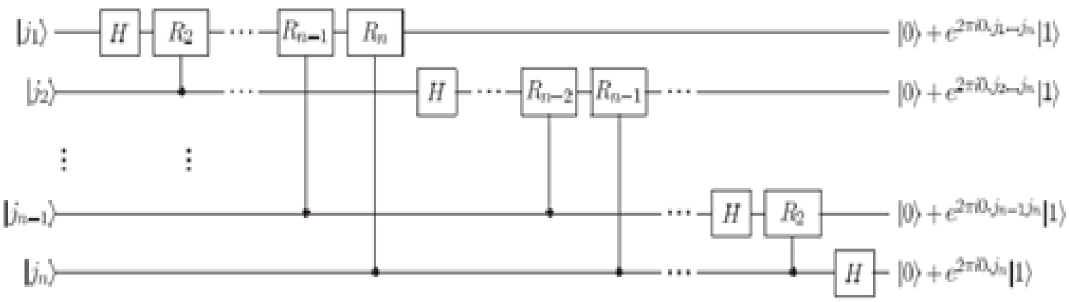


Fig 19 Circuit implementation of a QFT [RD-27].

5.5.2 Quantum algorithm

The proposed approach for defining a quantum algorithm for SAR image formation consists of a combination of data encoding, QFT and phase shift blocks. It takes as input a raw image, converts the image into quantum data using amplitude encoding, performs the whole processing chain in the quantum domain, and then converts the results into classical information through a measurement process.

5.5.3 Classical vs quantum architecture

The main challenge in defining a quantum approach for SAR image formation is that quantum circuits are based unitary operators. Performing a Fourier transform on a data vector encoded as amplitudes of quantum basis states has been shown to be a unitary operation. The QFT algorithm thus requires data in amplitude encoding form, adding an additional layer of data conversion from classical to quantum domain and vice versa. For the remaining steps, i.e., range compression, azimuth compression, and RCMC, an implementation compatible to the quantum circuit model must be chosen. For the above-mentioned RDA, according to our analysis, these steps can be interpreted as a chain of matrix multiplications, for which a corresponding quantum circuit block can be defined.

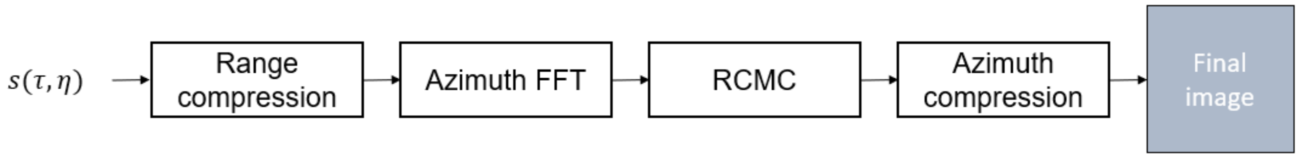


Fig 20 Range Doppler Algorithm: block diagram.

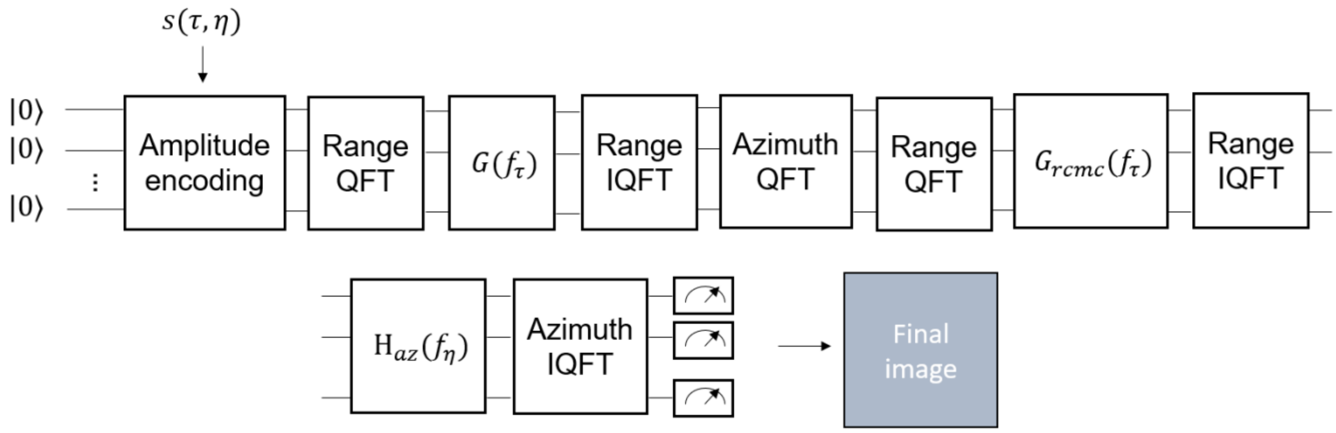


Fig 21 Quantum Range Doppler Algorithm: proposed quantum circuit approach.

5.5.4 Example of a problem instance

A SAR image dimension depends on multiple factors, i.e., extension of the analyzed area, bandwidth, PRF, ADC sampling frequency. Sentinel-1 works on multiple modes. The Stripmap (SM) products have a spatial resolution of 1.7x4.3 m to 3.6x4.9 m (range x azimuth). Considering a high-resolution image representing a 10 x 10 km area, the number of pixels would be 5882x2825=16616650. For encoding the real part of the data points using amplitude encoding, a circuit with $log_2(5882) + log_2(2825) = 24$ qubits is required. The circuit depth is related to the specific implementation of the blocks.

6 Conclusions

The following table summarizes the output of the WP1 listing the main features of the identified UCs:

USE CASE NAME	IMPACT ON EO	MISSION STEP	SIZING	CLASSIC SOLUTION	BOTTLE-NECKS	EXISTING QUANTUM SOLUTION	QUANTUM SPEEDUP	QUANTUM MATURITY WITHIN 15 YEARS
UC1 – Mission Planning for EO Acquisitions	medium-high	Mission analysis / data acquisition	Optimization problem whose research space scales a 2^N, with $N\sim10^9$	Genetic algorithms, simulated annealing	Quality of the solution for large constellations and time horizons > few days	yes	unknown	medium
UC2 - Multiple-view Geometry on Optical Images	medium	Data analysis	Images 30000 x 30000 x 4 (VHR)	Classical computer vision algorithms	Not solvable as one large optimization	yes	unknown	high
UC3 – Optical Satellite Data Analysis	high	Data analysis	Dependent on a variety of factors. A single training set sample of the time series ncludes 10 spectral bands multiplied by 5 dates, equating to a total of 50 features.	Machine learning algorithms like: random forest, SVM, neural networks	Kernel methods require the computa-tion of a kernel matrix, which is expensive for large datasets. There is a tradeoff between representa-tiveness and computa-tional cost.	yes	unknown	medium
UC4 –SAR Raw Data Processing	high	Data processing	Sar raw data consists of a complex matrix with ~ 40k x 20k entries (for STRIPMAP mode).	Range Doppler algorithm	Time, heavy computational burden for large images for FFT \ IFFT (each range line can have more than 20k points)	no	unknown	medium

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