High-Performance, Specialized and Quantum Computing for Remote Sensing. HDCRS – a New Working Group of the ESI Technical Committee

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The High-Performance and Disruptive Computing in Remote Sensing (HDCRS) Working Group (WG) was recently established under the IEEE Geoscience and Remote Sensing Society (GRSS) Earth Science Informatics (ESI) Technical Committee (TC) to connect a community of interdisciplinary researchers in Remote Sensing (RS) who are specialized on advanced computing technologies, parallel programming models and scalable algorithms. HDCRS focuses on three major research topics in the context of RS: (1) Supercomputing and Distributed Computing, (2) Specialized Hardware Computing and (3) Quantum Computing (QC). This article presents these computing technologies as they play a major role for the development of RS applications. HDCRS disseminates information and knowledge through educational events and publication activities which will also be introduced in this paper.

***Index Terms*—High Performance Computing, cloud computing, graphics processing unit (GPU), field-programmable gate array, quantum computing, edge computing, blockchain, geoscience and remote sensing.**

I. Introduction

Remote Sensing (RS) has come a long way since 1858, when Gaspard-Félix Tournachon captured the first aerial photograph from a hot air ballon over the Bièvre Valley in France [1]. At the beginning of 1972, Landsat data kickstarted the big data era by capturing images of the whole Earth's surface every two weeks [2]. The development of artificial satellites in the latter half of the 20th century allowed RS to progress to a global scale and monitor the entire planet in high-resolution, on-demand, and in near real-time.

Since 2008, with the emergence of the free and open data access policy for Landsat data [3] [4], many governments and space agencies have opened their archives making large collections of satellite RS data available to everyone (e.g., ESA's Copernicus [5]). RS was and further is a stimulating factor in the development of disruptive and High-Performance Computing (HPC) technologies. An example is the case of Synthetic Aperture Radar (SAR) image formation. SAR is an active coherent imaging system operated in the microwave domain. A SAR system records millions of samples per second. The transformation of the received echoes, i.e., the focusing process, requires application of matched filters principally involving the computation of Fourier transforms. In the early 1960's this a was major big data and HPC challenge stimulating the use and development of new technologies. Optical coherent processing was one of the first novelties at the time that HPC technology used [6]. Further at the end of 1970's SAR focusing was one of the applications for supercomputers. [7] presents the assessment of implementing a SAR processor on a CRAY-1 S Supercomputer. Today the implementation of quantum radars [8] and the use of quantum computers for further progress of the SAR data processing and analysis is studied.

Other RS big data are generated from a multitude of sources, including ground and airborne sensors (e.g., unmanned aerial vehicles (UAVs) [9]), social media, machine to machine (M2M) communications and crowdsourcing. Meanwhile, planetary-scale applications in earth science and environmental studies are further increasing the complexity of RS data. RS data can therefore be characterized by multi-source, multi-scale, high-dimensional, dynamic-state and nonlinear characteristics [10]. Processing such large amounts of complex data necessitates rapid development in innovative computing technologies and creating novel tools for addressing data storage challenges and improving data processing workflows.

An increasing number of research groups have been working in the field of high performance and cloud computing applied to RS, especially during the last few years [11][12]. The IEEE Geoscience and Remote Sensing Society (GRSS) is the right forum to foster bonds among these researchers and promote the use of these technologies by an ever-increasing community. The HDCRS WG was founded with these objectives. With its dedicated website, HDCRS disseminates information including the activities organized by its members. IEEE members can register as new members using the website.

The first activities of HDCRS were organized in 2021. These focus mainly on education and research promotion with the goal of creating a community. The group encourages members to promote their related initiatives. In particular, HDCRS organized its first summer school at the University of Iceland from 31 May to 3 June, 2021. The overall objective of the school was to give participants a comprehensive overview of current topics and methods in the field of High-Performance Computing (HPC), Machine Learning (ML), and QC in RS. A second objective was to establish a venue for students and young professionals to network with senior researchers and professors who are world-renowned leaders in the field of RS and work on the interdisciplinary research addressed by HDCRS.

The first edition took place online due to the pandemic conditions. Prof. Jón Atli Benediktsson, the rector of the University of Iceland, gave the opening remarks summarizing the opportunities offered within IEEE GRSS and their connection with the activities of the working group, which was presented by one of the chairs, Dr. Gabriele Cavallaro. The given lectures were organized in three thematic groups:

1) From HPC to Quantum Paradigms in Earth Observation (EO)
2) Programming Graphics Processing Units (GPUs) and Accelerators with Directives
3) Scaling machine learning for remote sensing using Cloud Computing

Out of 180 registrations from all over the world, the maximum number of 30 attendees were admitted in the Zoom sessions and received access to computing resources. The rest attended via YouTube live streams of the Zoom sessions. The recording of all lectures of the summer school is available on the GRSS YouTube Channel.

HDCRS was happy to receive very favorable feedback for the summer school and is looking forward to organizing the second edition as a physical event at the University of Iceland with several social activities. Registrations will open on the HDCRS's website on 1 March, 2022. It is envisioned that future editions of the summer school could be moved to other locations.

HDCRS has also organized two tutorials at the International Geoscience and Remote Sensing Symposium (IGARSS) conference. The first one was on "Scalable ML with High Performance and Cloud Computing" which provided a complete overview of supercomputing and cloud computing technologies for solving RS problems that require fast and highly scalable methods. The second tutorial "From Big EO Data to Digital Twins: Hybrid Artificial Intelligence (AI) and Quantum based Paradigms" covered quantum information theory, quantum algorithms and computers, presented the first results and analyzed the main perspectives for EO applications.

A special session at the IGARSS 2021 conference was also organized by HDCRS. Papers in the most advanced areas exploiting new high-performance and distributed computing technologies and algorithms to expedite the processing and analysis of big remote sensing data were collected. They included:

- Practice and Experience in using Parallel and Scalable Machine Learning in Remote Sensing from HPC over Cloud to Quantum Computing [13]
- Comparing Area-based and Feature-based Methods for Co-registration of Multispectral Bands on GPU [14]
- An FPGA-based Implementation of a Hyperspectral Anomaly Detection Algorithm for Real-Time Applications [15]
- Enhancing Large Batch Size Training of Deep Models for Remote Sensing Applications [16]
- Evolutionary Optimization of Neural Architectures in Remote Sensing Classification Problems [17]

HDCRS will organize new special sessions on different topics in the future editions of IGARSS.

II. HDRCS Research Topics

There is an increasing number of applications that benefit from the amount of data acquired by the most affordable and wide available RS sensors. Some of them require to be processed in real-time and most of them are complex, thus requiring high computational power. This requirement makes necessary the use of innovative computational approaches, from HPC platforms such as clusters, grids or clouds to accelerators such as GPUs or Field-Programmable Gate Arrays (FPGAs) or QC solutions, among others. The more adequate computing platform depends on the problem being solved and also on the environment where the problem needs to be solved. In some cases, for example, transferring data to supercomputers makes sense. In other cases, the problem is better to be solved in situ using commodity hardware. In this section, a perspective of the potential and emerging challenges of applying HPC paradigms to remote sensing problems is offered.

To solve a computational task, the first step is to split it into instructions that a processor can execute. The main objective is to process these instructions as fast as possible. This can be achieved in three different ways: to make the processor a. work harder (increase the raw power of the hardware, i.e., its clock speed on a single core, also referred as single-thread performance), b. work smarter (optimizing the task, use instruction level parallelism and exploit caching, etc.), or c. work in a team (more cores working in concert). While the first two strategies formed the basis of the main computing trend in the first fifty years of hardware computing the latter is currently the main trend.

The semiconductor industry have been shrinking the technology to try to follow Moore's Law: "... the number of transistors that can be inexpensively placed on integrated circuits is increasing exponentially, doubling approximately every two years ..." (Gordon Moore, 1965 [18]). The result was that by doubling the density of semiconductor over integrated circuits, the single-thread performance was constantly increasing. This trend was also identified by Robert H. Dennard, who in 1974 predicted that the power density (i.e., power dissipated per unit area) of transistors will remain constant while their size will continue to decrease [19] (i.e., as the physical parameters of transistors reduce they can be operated at lower voltage and thus at lower power). This means that it was possible to increase constantly the single-thread performance without raising the power consumption.

Dennard scaling (also knows as MOSFET scaling) started to reach its physical limits around 2004 to an extent that the voltage could not be scaled down as much as the gate's length of the transistor. This along with a rise in leakage current resulted in increased power density, rather than a constant power density (i.e., more heat generated which has to be dissipated through cooling solutions, as increase in temperature

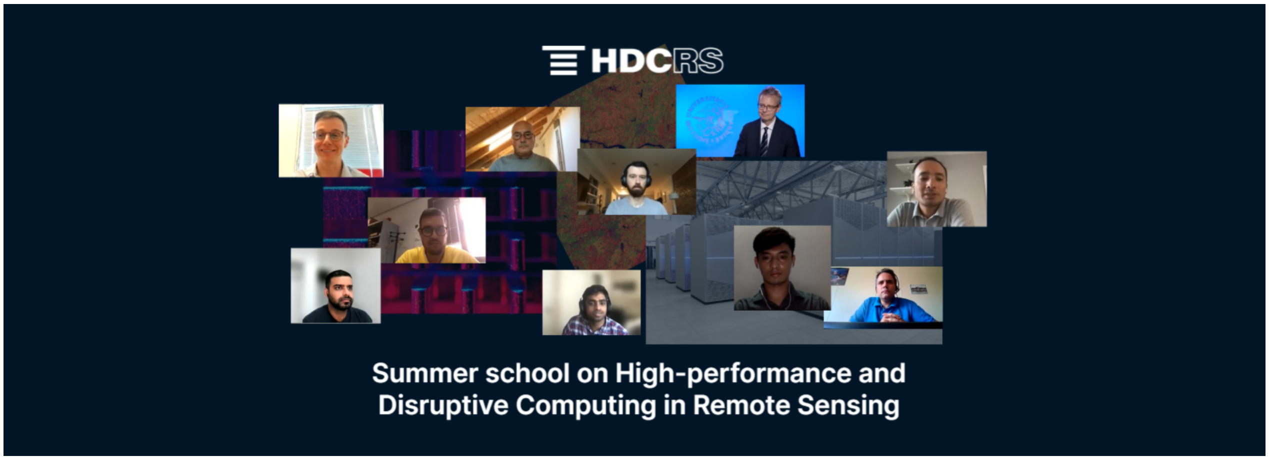

Fig. 1. The speakers of the 2021 HDCRS Summer School: Gabriele Cavallaro, Jón Atli Benediktsson, Mihai Datcu, Sergio Bernabé García, Carlos García Sánchez, Manil Maskey, Iksha Gurung, Muthukumaran Ramasubramanian, Shubhankar Gahlot and Drew Bollinger

beyond a certain level results in unreliable functionality of the chip). As a consequence, since early 2000, the single-thread performance improvements started plateauing as shown in Figure 2. This resulted in an unique situation in which Moore's law [18] was still holding, but the computing performance in return was no longer substantial as before [20].

Novel hardware architectures along with shifts in code paradigms became the focus of the industry in order to continue the same trends. Expanding the number of logical cores in Central Processing Units (CPUs) and shifting towards accelerators and co-processors which work on lower frequencies but have considerably higher amount of cores than CPUs proved to be the most significant move. The result was a mainstream shift of focus towards parallelization. Heterogeneous computing unifying different hardware architectures emerged as the most effective way to keep up with the need for ever higher computing performance.

In this context, the responsibility of reaching better computational performance is outsourced to software developers and programmers (i.e., algorithms need to be optimized to fully exploit new parallel computing environments).

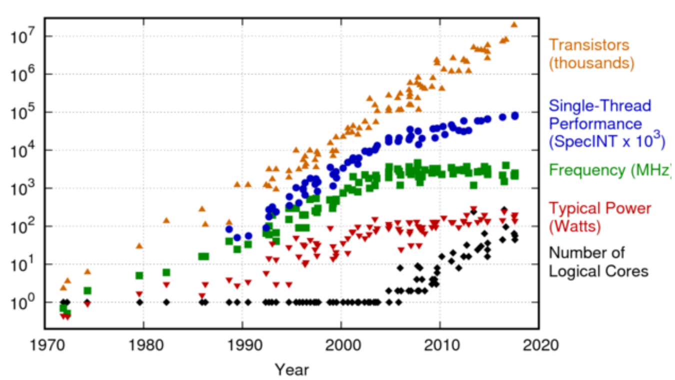

Fig. 2. 42 Years of Microprocessor Trend Data [21]. Orange points: Moore's Law trend. Around 2003, the clock speed curve (blue points: single thread performance) starts to flatten (i.e., Dennard scaling breakdown). Green and red points: immediate consequences of Dennard scaling breakdown; Black points: from 2003 the era of parallelism begins (i.e., obtain processing speed up with many cores).

In general, the development of parallel and scalable codes for complex algorithms is complicated and error-prone. It usually involves handling data slicing and distribution, task partition, message passing among distributed memory spaces and shared memory management for multicores, synchronization and communication with low-level APIs [22]. Nevertheless, as it was already shown ten years ago by Lee et al. [23], HPC and parallel programming are the only effective solutions that can address the computational challenges of data-intensive RS applications.

III. Research Topics

The essential concepts and principles, and the key techniques related to different computing technologies are elaborated in detail in this section. It describes how they enhance RS applications and provides future perspectives in the context of Earth Observation (EO).

A. *Supercomputing*

The action of solving processing tasks on a supercomputer is widely termed "supercomputing" and is synonymous with HPC. HPC is a multidisciplinary field of research that combines hardware technologies and architecture, operating systems, programming tools, software, and end-user problems and algorithms. It engages a class of electronic digital machines referred to as "supercomputers" to perform a wide array of computational problems or "applications" (alternatively "workloads") as fast as is possible. A supercomputer is a mixture of shared-memory and distributed-memory systems. While in a shared-memory system (i.e., desktop computer, laptop) a number of CPU cores have access to a common, shared physical address space, in a distributed-memory system each process is connected to exclusive local memory (i.e., no other process has direct access to it).

Supercomputers have been used in various fields of research since the 1980s [24]. At that time, a vector architecture was the mainstream and developers could improve the performance of programs by exploiting vector instructions. A vector instruction is a Single Instruction Multiple Data (SIMD) which refers to vector registers where multiple data resides. The first commercial supercomputer (i.e., Cray-1 [25]) included 8 registers, where each was a vector of 64 double-precision floating point numbers.

Single-thread exponential speed growth was the driving force of HPC in the first 25 years [21]. At first, each manufacturer of a distributed-memory system had its own library and set of functions that could do simple point-to-point communication as well as collective communication patterns like broadcasting. To simplify programming in network environments and to realize component-based software architectures, many models and portable libraries have emerged as possible standards (i.e., Distributed Component Object Model (DCOM) [26], Parallel Virtual Machine (PVM) [27] and Message Passing Interface (MPI) [28], etc.).

MPI was released in 1994 and developed as a standard library of defined message-passing. Since then, MPI became extremely successful and started to be adopted by many different scientific applications for distributing their computations on distribute-memory clusters (e.g., hydrogeology, traffic simulation, weather forecast, etc. [29]). MPI became the de facto standard for parallel scientific computing and it is the most mature methods currently used in parallel programming.

Supercomputers have been widely used in RS applications to accelerate and scale the process of image mosaicking [30] [31], classification [32] [33] [34] [35] [36] [37], object detection [38] [39], clustering [40] [41] [42], interband registration [43], super-resolution [44], data fusion [16], compression [45], feature selection/extraction [46] [47] [48], spectral unmixing [49], data assimilation [50] and scalable processing workflows [51] [52] [53] [54] [55] [56]. In the context of HPC, there were also important efforts in academic journals and conferences launching multiple special issues devoted to the processing and analysis of RS data [57], [58], [59], [60].

The next generation of supercomputers (i.e., Exascale supecomputers) will be used to model and simulate more complex and dynamic systems in higher resolution and with unprecedented fidelity (e.g., biological systems, molecular interactions of viruses, material design, etc.). In the context of EO, Exascale supecomputers will enable the development of a high precision digital model of the Earth (i.e., Destination Earth [61]). This will help analyze with very high precision the effects of the climate change together with possible adaptation and mitigation strategies (e.g., to predict major environmental degradation and natural disasters with unprecedented fidelity and reliability).

B. Cloud Computing

Cloud computing is an overarching term that describes a category of on-demand computing services [62]. These services were initially offered by commercial companies such as Amazon, Microsoft, and Google. Now, there are many new commercial and public cloud computing providers. The underlying principle behind cloud computing is the idea of providing access to storage, compute, and software "as a service" that may not be on premise. Common characteristics of cloud computing include: (i) elasticity: defined as the ability to scale resources both up and down as needed, (ii) reliability: implies that the service is available and works as intended, (iii) pay-as-you-go: users only pay for what they use, (iv) resource pooling: allows cloud provider to serve its users in a multi-tenant model, and (v) minimal management effort: users can use and procure cloud service without much difficulty.

The concept of cloud computing is not new. Grid computing [63], which was introduced in the 1990s, included a type of parallel and distributed system that enabled the sharing of geographically distributed resources. The power of grid computing was enabled by the ability to dynamically scale up and down the resources based on the user's need. The concept of grid computing evolved to solve large-scale processing workloads that required more than a single computer. Cloud computing automated some of the nuances of grid computing, specifically in the area of virtualization and on-demand scaling. Compared to the grid computing approach, which requires allocation of resources in advance, cloud computing is more attractive since real time provisioning of resources is possible.

As the cloud computing has advanced, main services offered by most providers have evolved into three classes, based on the abstraction level of the capability that they provide: (i) Infrastructure as a Service (IaaS), (ii) Platform as a Service (PaaS), and (iii) Software as a Service (SaaS) [62].

Figure 3 depicts the three layers, which shows the stacked organization from the infrastructure to the application layer. Each higher layer can utilize the services from the bottom layers.

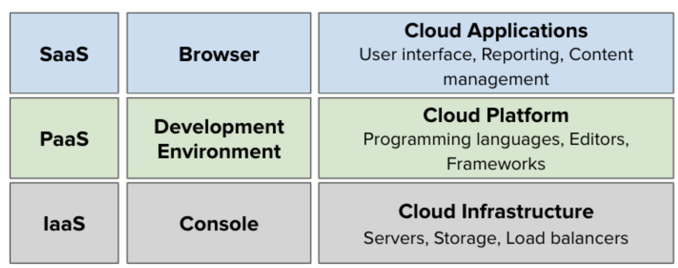

Fig. 3. Cloud services - a layered view.

IaaS uses virtualization technology to deliver computation, storage, and networking on demand. Cloud providers enable on-demand provisioning of servers which can be used to develop applications. Users of IaaS will require system administration knowledge and usually have full control over the virtualized machine. Amazon Elastic Compute Cloud (EC2, http://aws.amazon.com/ec2/) is an example of IaaS.

PaaS is an environment where users can create customized solutions using tools and services that the platform provides. This layer is at a higher level of abstraction which makes a cloud easily programmable. Often a PaaS tool is a fully integrated development environment–all the tools and services are part of the PaaS service, which supports a complete lifecycle of building and deploying applications. Google App Engine is an example of PaaS.

SaaS is the complete cloud computing service model where the computing hardware, software, and a particular solution itself, are provided by a vendor as a complete service offering. Services provided by this layer can be accessed by end users through browsers. For this reason, most users are increasingly shifting to on-line software services. The ArcGIS implementation on the cloud is an example of Software as a Service (SaaS).

With the advances in sensor technology and highly competitive and vibrant space industry, the RS data is being collected at massive scale. Moreover, there are upcoming missions with higher spatial, spectral, and temporal resolution which poses challenges in not only storing the data but also processing needs. To address these challenges, many agencies have already explored cloud computing as a viable solution. Cloud computing provides elasticity in storage and computing that traditional data centers cannot support. Cloud computing also facilitates large-scale scientific processing enabled by the cloud-native services that are collocated with the data. During last two decades, there has been accelerated adoption of cloud computing within RS community. The trend of this adoption can be observed with the number of publications by major RS research publishers that are related to cloud computing.

The National Aeronautics and Space Administration (NASA) has started migration of its Earth science data to the cloud computing environment [1] to support the large data volume missions that will be launched in near future. Towards that end, NASA has developed a generalized cloud-native ingest archive pipeline called Cumulus [64]. In the meantime, there are parallel efforts to train scientists to perform scientific analysis in cloud computing environments, since it is more economical to perform analysis in the cloud than downloading a large amount of data from the cloud to on-premise. Hence, cloud computing has also emerged as the analysis and processing platform for many applications [65]. In RS, there are many examples of data processing frameworks developed in cloud computing [66][67][68][69][70]. In fact, many new RS data products are being generated using cloud computing [2]. Cloud computing has also advanced data storage and access techniques of RS datasets. Such advances have allowed dynamic data visualization and analysis which are otherwise not possible [71][72]. Finally, development of end-to-end RS based situational awareness tools [73] are enabled by cloud-native services that are capable of delivering reliable and on-demand needs.

With cloud computing, any researcher around the world is able to use a browser and open RS data to perform scientific research. RS has specially benefited from cloud computing and many existing legacy applications have the potential to adapt to and take advantage of cloud capabilities. However, there are challenges in adopting the cloud. These challenges include security, evolving cloud-native services, multi-cloud portability, and learning curve required to perform science on cloud.

[1]https://earthdata.nasa.gov/eosdis/cloud-evolution

[2]https://earthdata.nasa.gov/learn/articles/hls-cloud-efforts

C. Specialized Hardware Computing

Numerous research efforts have been directed towards the incorporation of specialized hardware for accelerating RS-related applications during the last decade [74], [75], [76]. The emergence of specialized hardware devices such as Field-Programmable Gate Arrays (FPGAs) [77] or GPUs [78] exhibited the potential to bridge the gap towards on-board and fast on-the-ground analysis of RS data. The small size and relatively low cost of these devices as compared to clusters or networks of computers makes them very appealing for parallel computing in general and for RS in particular. GPUs can also significantly increase the computational power of cluster-based systems and, nowadays, they can be found in the most powerful non-distributed computer systems in the world [3]. In the case of FPGAs, the main advantage is the configurability, although they are generally more expensive than GPUs (see Figure 4).

FPGAs have consolidated as the standard choice for on-board RS image processing due to their programmable nature, dynamic reconfiguration capabilities, smaller size, weight and power consumption, as well as for the existence of radiation-hardened and radiation-tolerant FPGAs [79], [80], [81], [82]. However, these devices are more expensive, physically larger and are often technology generations behind in both performance and functionality than their commercial counterparts [79], [80]. For this reason, the current trend for small satellites is to use Commercial Off-The-Shelf (COTS) onboard electronic devices. Moreover, commercial FPGAs based on Static Random Access Memory (SRAM) are attracting attention because of their reconfiguration capabilities and low cost compared to Application Specific Integrated Circuits (ASICs) [83]. Nonetheless, the use of COTS devices implies the necessity of applying mitigation techniques in order to increase the robustness of the application performance in environments exposed to radiation. In this sense, different Radiation Hardened By Design (RHBD) strategies have been developed over the years to protect the FPGA-based designs against radiation [84], [85], [86], such as Dual Modular Redundancy (DMR) schemes for detecting errors and Triple Modular Redundancy (TMR) designs for error masking.

Although recent literature features plenty of works related to the utilization of FPGA devices for real-time onboard processing (including classification, detection, and spectral unmixing [88], [89] among many other processes such as hyperspectral image classification [90], [91],) the more significant advances have been achieved in the field of on-board compression. In fact, developing efficient compression solutions for space supposes a challenge. The employed algorithms must achieve the goal in terms of compression ratio while at the same time they should have low complexity to be executed on the available hardware resources on-board satellites and the required timing performance to meet mission requirements.

There is an immense quantity of contributions to the field of FPGA implementations for on-board data and image compression, both on COTS and RHBD devices. Of particular focus are those that follow the compression techniques proposed by

[3]http://top500.org

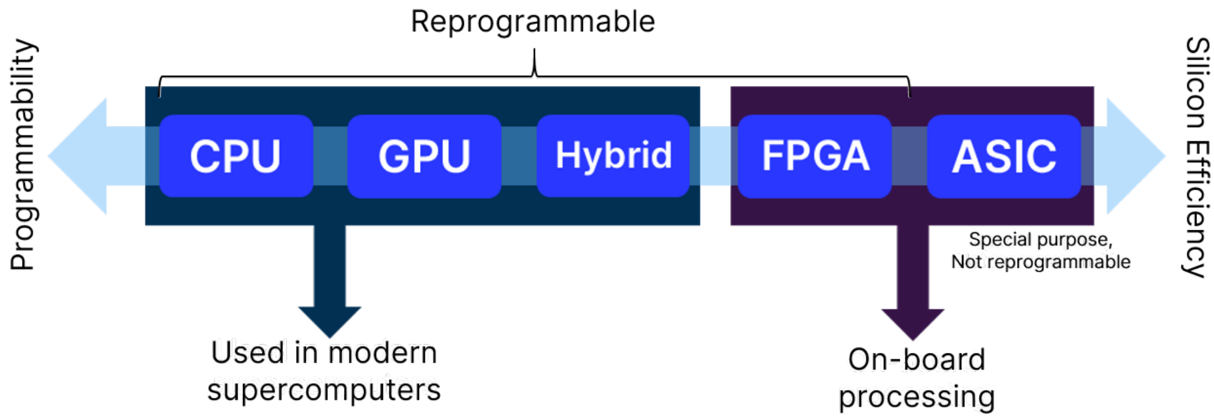

Fig. 4. Programmability versus performance tradeoff of computing devices [87].

the Consultative Committee for Space Data Systems (CCSDS), an international organization comprised by the main space agencies in the world to define a common way for developing space data and information systems. Within these implementations, it is worth highlighting the works that implement the CCSDS 121.0-B-2 data compression standard [92], [93], which is based on Rice coding, onto space-qualified FPGAs, as well as those that implement the CCSDS 123.0-B-1 lossless hyperspectral image compression standard both in COTS and RHBD FPGAs [94], [95], [96], [97], [82].

Although GPUs had traditionally been limited to graphical operations, during the last decades they progressively evolved into a highly parallel, multithreaded, many-core processors with tremendous computational speed and very high memory bandwidth [98]. In GPUs, more transistors are devoted to data processing rather than to data caching and flow control. With the release of NVidia CUDA [4] in 2007 and OpenCL [99] in 2009, the programming model for GPU was greatly simplified introducing the possibility of including GPUs in many science and engineering applications. CUDA is an extension to the C programming language offering programming capabilities of GPUs for general-purpose computation (GPGPU). OpenCL was developed by a consortium and released in 2009. It aims at supporting more hardware and to provide a standard for general purpose parallel programming across CPUs, GPUs, and other processors [99]. Nowadays, the combined features of general-purpose supercomputing, high parallelism, high memory bandwidth and low cost makes a GPU-based computer an appealing alternative to a massively parallel system made up of only CPUs [100], [75].

The first developments in CUDA presented highly coupled and non-reusable GPU parallel strategies. Many efforts were made for developing parallel programming templates [101] and libraries [5] to simplify the programming task. The extraordinary evolution in this aspect during the last few years has motivated the extended use of GPUs for accelerating many different RS and, in particular, hyperspectral imaging-related tasks [74], [100], [75], [102], [103], [76]. These include registration [104], [14], segmentation [105], classification [76] or change detection [106], among others.

Based on the capability to execute thousands of threads in parallel, the primitives such as the inner and outer products can perform better in the CUDA platform, so ML and, in particular, deep learning algorithms, formed by these primitives benefit from the computational capacity of CUDA [103]. For example, The CNN convolution, pooling, and activation calculation operations are readily portable to GPUs [107]. In this context, many tools have been developed to automatize the programming and execution of deep learning algorithms in GPU-based architectures among which TensorFlow is the most popular option [108]. This has contributed to the extensive use of GPUs for deep learning applied to RS for many operations [109], [110] including, for example, object detection [111] or classification [112] [113] [114] [115], [116].

As explained above, FPGAs and GPUs clearly help in processing RS data by accelerating computations and providing solutions for time critical applications on-board and on-ground, which opens a wide variety of use cases related to Earth monitoring. Benefiting from them requires the careful selection of the algorithms which better adapt to the FPGA and GPU architectures. For the particular case of GPUs, many papers present algorithms and techniques adapted to it, as mentioned in the previous paragraphs, but GPUs are not being extensively exploited yet. More research is required for the development of new techniques, algorithms and applications exploiting all the potential for execution time improvement that the wide variety of systems using GPUs offer.

D. Edge Computing

With the rapid advance in Internet of Things (IoT) technology, the number of network edge devices and the amount of data generated by edge devices have shown explosive growth in recent years. Due to the limited network communication capacity, the centralized processing mode in cloud computing may not be able to process massive data efficiently and quickly.

In 2013, the concept of edge computing was firstly mentioned by Ryan Lamothe of Pacific Northwest National Laboratory. In 2016, Weisong Shi proposed that edge computing

[4] http://developer.nvidia.com

[5] https://docs.nvidia.com/cuda/

refers to the technologies computing at the edge of the network. This includes the processing of downstream data and upstream data by cloud services and IoT services, respectively [117].

Generally, edge computing has two operation modes: 1) Binary offloading: A deeply integrated or comparatively simple computing task cannot be divided and has to run either directly on the edge device or offloaded to the cloud. 2) Partial offloading: Part of the tasks originally located in the cloud data center are allowed to be offloaded to the edge of the network. Through the two operation modes, edge computing can flexibly adjust the load of cloud and edge servers via offloading so as to realize the requirements of massive connection and low response delay of IoT devices. In certain cases, users can save more than 30% of the cost of computation, storage, and bandwidth. Mobile edge servers can also control the proximity between edge devices and the terminal users, so that they can track real-time information of the terminal users such as action, location and environment. In addition, mobile edge computing (MEC) can protect the privacy and enhance the security of mobile applications [118].

Benefiting from the advantages on low latency, low power and strong privacy, edge computing has attracted wide attention from researchers and it has been widely used in industrial fields such as autonomous driving environment monitoring, intelligent home virtual enhancement, medical and health industry production, etc. For example, in the field of autonomous driving, a car does not need to send all the generated data to the cloud for processing. Most of the data is stored and calculated at the edge nodes (i.e., the car itself).

Although it is effective in reducing computing delay and power consumption, edge computing is also facing new challenges. First, limited by the computing capacity of edge devices, the accuracy of calculation results needs to be further improved. Second, most of the devices in edge computing are heterogeneous computing platforms, and the operating environment and data on each device are quite different. Therefore, it is challenging to deploy user applications in edge computing scenarios. In addition, as of yet, there are no comprehensive and uniform benchmarks for evaluating system performance.

Edge computing has been widely used in various fields of RS. Since the computing capacity of most edge devices is limited, the most common use of edge computing in RS applications is data preprocessing, which is able to mitigate the transmission pressure and decrease the computing cost in the cloud. In [119], a multiple industrial IoT system architecture based on unmanned aerial vehicles (UAVs) is proposed, in which the RS images collected by sensors in the industrial IoT is directly transmitted to the UAVs for processing. Based on the RS image analysis and neural computation model, the authors in [120] built a forest ecotourism evaluation scheme and designed a cloud-based mobile edge computing model to construct efficient prediction scenarios [120]. In [121], the image recognition performance of hierarchical discriminant analysis (HDA) algorithm was implemented by combining edge computing environment with (HDA) algorithm for early warning of mountain fire.

With the increasing applications of edge computing in RS, there are many aspects that need to be further researched. Firstly, the performance of edge equipment, the ability to collect RS information and data processing need to be strenghtened so as to promote the accuracy of edge calculation result. Secondly, cloud-edge offloading strategies for RS need to be proposed to allocate computing resources more reasonably, so as to reduce computing delay and power consumption in RS applications.

E. Quantum Computing

At the beginning of the 1980’s Richard Feynman [122] observed that numerical simulation of quantum mechanical systems requires an exponentially-growing – with the quantum mechanical system dimension – amount of such computational resources as CPU time and memory. This observation has led to a conclusion that for the simulation of quantum mechanical systems one should employ easily controllable quantum devices whose complexity can grow sub-exponentially with the growth of the quantum mechanical system dimension. Such easily controllable device was named by Feynman a quantum computer. The first formal formulation of Quantum Computing (QC) was proposed in 1985 by David Deutsch [123]. In 1992 Deutsch and Richard Jozsa proposed the first quantum algorithm that could outperform the classical counterpart [124]. In the following years many other important quantum algorithms were proposed such as the Shor’s algorithm for factoring integers [125], [126], Grover’s search algorithm [127] and the Harrow-Hassidim-Lloyd algorithm for solving a linear system of equations [128].

Quantum computers can be understood as being analog and digital at the same time. Analog – because the state space of quantum devices during the computation process can be described by a set of continuous variables, digital – because the measurement outcome from a quantum computer can be expressed as a binary string. Quantum computers, as most of analog computers, are prone to errors. Due to the uncontrolled interaction with the environment a state of a quantum computer can become distorted during the computation process. This phenomenon is called quantum decoherence [129]. Fortunately, the influence of decoherence can be reduced by the use of quantum error correcting codes. These codes employ multiple physical qubits to form a single logical qubit [130] and use the digital aspect of the quantum measurement to correct quantum errors.

Currently, quantum computers have reached the so called Near Intermediate-Scale Quantum era [131]. This means that they consist of about a hundred noisy qubits and therefore classical computers are unable to simulate them efficiently. Simultaneously it is only possible to perform short quantum programs before the quantum state becomes so distorted that it is no longer useful. Hence, it is impossible to execute such algorithms as Shors’ and Grover’s using current quantum hardware.

Currently, two paradigms of QC are implemented in the hardware. The first one is the so called universal gate-based QC and the second one is quantum annealing. Gate-based quantum computing is currently mostly used to execute variational quantum computing algorithms [132] – a class of algorithms that use quantum computer as a co-processor to execute computationally costly subroutines in which a value of a quantum observable for a particular state generated by a parametrized quantum circuit is estimated. In variational quantum algorithms the parameters of the quantum circuit are optimized in an iterative process using a classical optimization technique. Variational quantum algorithms find applications in combinatorial optimization problems, finding low-energy states of molecules and in ML.

Quantum annealing [133] is a heuristic computation method that implements approximately the adiabatic quantum computing model. This model allows finding good approximate solutions to Quadratic Unconstrained Binary Optimization problems [134]. This is a class of computationally hard problems that find applications in logistics, scheduling, image processing and ML among others.

Even though the quantum advantage – solving a particular computational task impossible to solve classically by way of using quantum computer – was claimed by Google [135] in 2019, currently existing quantum computers have no practical applications yet. Fortunately, the field is progressing fast both in terms of algorithm and hardware development.

Quantum Machine Learning (QML) [136], [137] is a term that can encapsulate both the techniques of using quantum computers as ML subroutines during training and inference or using quantum computers to help training of classical classifiers. QML is currently a very active area of research that, hopefully, could allow to build better models for a variety of ML tasks.

In the field of RS there are particular applications of QC that were developed recently. For example in [138], [139], [140], [141] QML algorithms such as the Support Vector Machine (SVM) and neural networks are applied for classification of multispectral images. In [142] the authors use a quantum annealer to perform three following tasks on hyperspectral data: classification using a variant of SVM, band selection for classification and boosting of classical classifiers. Outside the applications to hyperspectral imaging the authors of [143] proposed a classification method for Synthetic Aperture Radar images using a hybrid quantum-classical neural network.

Today the European Space Agency (ESA) considers quantum computing and AI taking the centre stage for the implementation of the Digital Twin Earth (DTE) [6]. While quantum computing technology concepts are broadening and growing in the qubit capacities, the applications in RS and QML may have unexpected results. The analysis of the data complexity, and the identification of optimal data embedding may open novel perspectives. For example signatures of satellite images could be encoded as quantum states and transformed using for instance quantum kernels for classification. It might be feasible to encode a time varying sequence of EO images on a quantum state and analyse it using a quantum computer in order to understand the change of the Earth surface. But to achieve that, more efforts in both the theoretical development of quantum algorithms and quantum hardware design and production will have to be made in order to push the boundaries of what is possible to achieve with quantum computing. An important aspect is the close collaboration with the quantum computer developers and providing appropriate requirements (e.g., European Quantum Industry Consortium (QuIC) [7]).

F. Blockchain

Open data became a significant vector in all services consumed nowadays, as enormous quantity of data are quickly accessible. Most of the times, distributing and retrieving data is drained through mediators which impose control and evaluation policies for reliability and integrity of the data. As connections between data owners and data consumers are generally maintained through a central authority for practical goals, limiting the actions of the users, intermediary technologies are necessary to ensure trust among participants, data availability, data validity, and data integrity, all in a transparent way.

The advent of technological progress and evolution in open-source and Distributed Ledger Technologies (DLT) demonstrated that it is possible to develop systems that prioritize individual jurisdiction over centralized control. Distributed ledgers are collections of replicated, shared, and synchronized digital records that are stored across multiple geographically disseminated sites. A blockchain, an example of DLT, is fundamentally an append-only permanent verifiable data structure maintained by a set of nodes that do not fully trust each other. These nodes comply on a set of global states for an ordered collection of blocks, each containing multiple verification records (i.e., transactions). Each block is linked in a chain of blocks where the subsequent block has additionally a verification record of the previous block (i.e., a unique hash fingerprint). In this way, it is impossible to add new information to older blocks in the chain without changing the subsequent blocks. Each node keeps replicas of the data and grants on an execution order, thus producing an immutable log of ordered transactions within a distributed transaction management context.

Blockchains have manifested great promise in several fields like cryptocurrency (Bitcoin [144], Ethereum [145], etc.), governance, land registration, justice, identity management, asset-tracking, IoT to name a few, materializing in large-scale adoption as the result of solving limitations in previous systems. The blockchain technology also started to evolve within the new space sector (i.e., Space 4.0) over a range of potential applications, from satellite communications to procurement. In a whitepaper, ESA accentuated the relevance of assimilating blockchain in RS applications [146], supporting action automations through smart contracts and transfer of value without a pivotal authority. Data gathered via close-range sensors, e.g., IoT sensor networks or personal drones can massively enrich EO applications in consistency and accuracy.

[6]ESA ϕ-week, 2020: https://www.esa.int/Applications/Observing_the_Earth/Digital_Twin_Earth_quantum_computing_and_AI_take_centre_stage_at_ESA_s_Ph-week

[7]European Quantum Industry Consortium (QuIC): https://qt.eu/about-quantum-flagship/the-quantum-flagship-community/quic/

Data owners can keep ownership providing reliability through a blockchain solution.

Due to verifiable and immutable nature of blockchain technology, it can be used as a distributed database of digital fingerprints (e.g., mapping, cadastre and land registration [147], sharing continuously updated ML models [148], etc.) As corruption can be a big challenge within administrative systems, registration of land and real-estate ownership using blockchain enhances transparency and accountability, bringing actors in control of their own data. Enormous repositories of data are transformed in intrinsically public open data by adopting blockchain and related technologies like IPFS [149], where no one controls data, anyone can access data, and anyone can audit the entire history of inputs. Novel blockchain protocols can also be used to precisely map physical world events in a temporal progression. For instance, Crypto-Spatial Coordinate (CSC) is an open and interoperable standard for location in Ethereum smart contracts. FOAM [150] is a CSC blockchain protocol that preserves geo-spatial data by validating proof of location associated with the entry's specific time.

Blockchain technology brings important contributions in process management within complex systems, offering capabilities of managing massive patterns of transactions in any combination of two entities, human and device. SpaceChain builds an open source satellite network [151] in which satellites incorporate blockchain as an operating system and interface for decentralized applications in order to permit individuals to work on collaborative projects, with smart contracts on a space-based computing platform.

Blockchain can improve space communications and navigation, where risk of transmission disruption can be eliminated by developing a decentralized, secure, and cognitive networking and computing infrastructure for deep space exploration [152]. A decentralized schema for verifying satellite locations in time, through a type of proof-of-location protocol is proposed in [153]. The intent in using a permissioned blockchain is to facilitate scalability and trustless cooperation between satellite operators. Deployment and operation of small satellite constellations may encounter obstacles as satellite communications can be significantly delayed. In this case, occasionally, cryptographically-secure telemetry-based challenges are completed by satellites in order to verify the correctness of each other's position [154].

Blockchain solution brings advantageous capabilities in data traceability and data reproducibility. A secure way of tracking down the changes made to the source data of Sentinel-2 satellite is considered in [155]. The author proposed a system that captures each modification made to the original data set with the aim of being able to perform trace back and intermediate verification. In this design, data storage and data degradation problems still exist.

The synergy between blockchain and RS technologies is still fragile and sometimes divergent, but dynamics of technological interaction sustains an evolving symbiosis and finds RS use cases in space asset tracking [156], space communications as well as precision agriculture [157] among others. Blockchain-based RS data sharing model seems to be an applicable service that generates properties like immutability, decentralization, security, credibility and collective maintenance, indispensable in communications between RS actors.

IV. Conclusion

As the availability of sensors producing high amounts of RS data has increased, new applications of RS have emerged. The requirement of rapid and effective solutions for the processiong of this massive data has led to the extended use of parallel execution. This paper introduced HDCRS, which is a working group of the IEEE GRSS founded at the beginning of 2021 with the aim of promoting research, education and job opportunities in the interdisciplinary field of RS and high-performance and disruptive computing. The key technologies involved in RS parallel computation – in particular super-computing, cloud computing, specialized hardware computing, quantum computing, edge computing and blockchain – are also presented. The most recent literature shows that new research is rapidly maturing at the intersection of the very different disciplines of RS and high performance computing.

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