Research Progress on Models, Algorithms, and Systems for Remote Sensing Spatial-Temporal Big Data Processing

Yang Liu, Lanxue Dang, Shenshen Li, Kun Cai, and Xianyu Zuo

Abstract—**With the rapid development of high-resolution earth observation systems, the data processing, algorithm design, and system development of remote sensing spatial-temporal big data (RS-STBD) have gradually become the bottleneck problems in the application and development of earth observation system. The research on the model, algorithm, and system of RS-STBD processing involves complex scientific problems, technical bottlenecks, and inconstant requirements of engineering applications. This article summarizes the data type and processing theory model of RS-STBD, the high-performance algorithm design based on cloud service and intelligent computing, and the architecture design and engineering development methods of the complex remote sensing application system. Furthermore, the existing problems in the current research are analyzed, and the related solutions are given. Finally, the future development trend of scientific exploration, technical research, and application development of RS-STBD has prospected.**

Index Terms—**Remote sensing spatial-temporal big data, spatial-temporal data model, remote sensing cloud computing, remote sensing algorithm, remote sensing system architecture, high-resolution earth observation system.**

I. Introduction

IT IS a kind of spatial-temporal big data (STBD) that the data acquired by remote sensing (RS) information system, geographic information system (GIS), geological information system, smart city system, traffic information system, environmental information system, meteorological information system, and other complex systems. As an important source of information extraction, RS data are a typical STBD with temporal dimensions and spatial dimensions, meanwhile, which contain the observation information and spatial-temporal attributes of ground objects. The essence of RS data is the space-time sampling of the ground object by the RS information system, which uses different temporal resolutions, spatial resolutions, radiation resolutions, and spectral resolutions. RS is an irreplaceable global observation tool, with the advantages of macrodynamics, and has become the basic technical support for the implementation of sustainable development strategy [1].

As a strategic and forward-looking infrastructure of national major science and technology, RS system engineering involves RS platform, data acquisition systems, information processing systems, and knowledge application systems. In 1980, NASA proposed the U.S. Global Change Research Program and established the earth observation system (EOS) in 1991 [2]. With the development of science, technology, and engineering of RS, a high-resolution earth observation system (HREOS) has been built in the world now. In 2013, China's long-term scientific and technological development (2006–2020) launched a major project of China's high-resolution earth observation system (CHEOS) [3], which is planned to be initially completed around 2020. However, with the development of global HREOS, the efficient and rapid processing of remote sensing spatial-temporal big data (RS-STBD) has gradually become the bottleneck of its application [4]. Therefore, it is necessary to explore the frontier scientific issues, common key technologies, and engineering application bottlenecks in the construction of HREOS, and sort out the research progress of models, algorithms, and systems for RS-STBD processing.

For the processing of RS-STBD, this article focuses on the data model and processing model of RS-STBD, as well as the research progress of RS algorithm and system application. The remainder of this article is structured as follows. Section II summarizes the existing theoretical model of RS-STBD. Section III introduces the typical RS algorithm and process controls technology. Section IV reviews the latest architecture of information processing, RS data, and product distribution system. Section V presents the current RS system engineering and complex application system. Finally, In Section VI, the existing problems and solutions are given, and conclude this article and provide recommendations for future development work.

II. Theoretical Model of RS Processing

The observation data of RS sensors generally include matter information of electromagnetic, optics, and acoustic detection, such as the intensity, degree of polarization, and phase difference of acoustic, optical, and electromagnetic waves [5]. Using the

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TABLE I
CLASSIFICATION OF COMMON SPATIAL-TEMPORAL DATA MODELS AND SPATIAL-TEMPORAL TARGET MODELS

Classification Methods	Types of Spatial-temporal Models	Typical Models
Classification based on spatial-temporal object description	Temporal snapshots of entity state description	Space-time cube model [12], sequent snapshots model [13], base state modification model[14],discrete grid cell table model [15],space-time composite model[16], 1NF spatial-temporal data model, N1NF spatial-temporal data model[17] etc.
	Object change represents that the relationship before and after entity change	Object-oriented data model, graph theory based spatial-temporal data model, process oriented spatial-temporal data model [18], cellular automata [19] etc.
	Events and actions of semantic relation of entity's spatial-temporal change	Event based spatial-temporal model [20],three domain model based on spatial-temporal and semantic[21], ontology based spatial-temporal data model [22] etc.
Classification based on spatial-temporal data structure	Storage model	Multi-mode tensor expression model [23] etc.
	Logical model	Three domain model, Object-oriented data model, 1NF spatial-temporal data model, N1NF spatial-temporal data model etc.
	Conceptual model	Sequent snapshots model, discrete grid cell table model, base state modification model, space-time cube model, space-time composite model, Event based spatial-temporal model etc.

TABLE II
COMMON SYSTEM ARCHITECTURE FOR RS SOFTWARE

Architecture features	Layered architecture	Event driven architecture	Micro-kernel architecture	Micro-service architecture
Overall Agility	Low	High	High	High
Ease of Deploy	Low	High	High	High
Testability	High	Low	High	High
Scalability	Low	High	High	High
Ease of Development	Easy	Low	Low	High
Performance	Low	High	High	Low

functional relationship between measurable data and target state, the RS model can be constructed to retrieve and obtain the physical [6], chemical [7], or biological [8] target information from the RS measured data. Efficient RS-STBD processing involves RS data model, RS processing theory, RS inversion model, RS processing workflow, and other theoretical models.

The processing of RS-STBD involves the representation and organization of RS data, storage, and distribution of RS data, intelligent processing, and data mining theory of RS data. Here, the representation and organization of STBD are the basis of data precision and information extraction of RS data; the storage and distribution of STBD are the premise of implementing RS service; the intelligent processing and mining of STBD are the guarantee of RS socialized application. RS-STDB model is the theoretical basis of RS information extraction and processing, temporal geographic information system (TGIS) [9], and global position system (GPS). The RS-STBD model includes describing the structure model of spatial-temporal data, describing the information model of spatial-temporal objects, the intelligent computing model of RS, the spatial-temporal analysis, and the processing model of RS.

A. *Commonly Used High-Resolution Satellite and RS Data*

At present, the development of satellite RS has formed three independent and interrelated systems: commonweal RS system, commercial RS system, and military RS system. With the development of HREOS, the system has produced a large number of data with the technical characteristics of the diversified observation methods, diverse observation objects, and various information acquisition capabilities [10]. Generally speaking, the payload of the satellite of HREOS covers the main RS bands including visible light, infrared, ultraviolet, microwave, etc., and forms a full band detection capability. The main satellite RS data and parameters of the global HREOS are described in Tables III–VI. Currently, RS-STBD with large capacity, multitype, high dimension, multiscale, and nonstationary has been formed, which has 5H (high spatial resolution, high temporal resolution, hyperspectral resolution, and high radiation resolution) characteristics [11].

B. *Target Information Model and Data Structure Model of RS-STBD*

As given in Table I, the spatial-temporal models of target mainly include spatial-temporal state model of target, spatial-temporal change model of target, and spatial-temporal relationship model of target. The spatial-temporal state model of target separates the spatiotemporal object from the concrete space and time state, which reflects the independence of space and time relative to the object. The space-time state triples are used to describe the target state. State: $= (O, S, T)$, $O \in OBJ$, $S \in SPACE$, $T \in TIME$; OBJ, SPACE, and TIME are object domain, space domain, and time domain, respectively. The spatial-temporal change model of target is the change of attribute, position, and shape of spatiotemporal entity, or the change of topological relationship. The spatial-temporal change is complex, and the object variable, space variable, and time variable can change independently in their respective domains. The spatial-temporal relationship model of the target is a spatial-temporal model based on the object-oriented spatial-temporal relationship.

Spatial-temporal data model, which describes data structure, includes storage model, logical model, and conceptual model. At present, the existing spatial-temporal data model and spatial-temporal target model have achieved fruitful results, for example, the space-time cube model [12], sequent snapshots model [13], space-time composite model [16], cellular automata [19], multimode tensor expression model [23], three-domain model [21] based on spatial-temporal and semantic, event-based spatial-temporal model [20], object-oriented data model, process-oriented spatial-temporal data model [18], ontology-based spatial-temporal data model [22], and the improved models of these models. Throughout the development of the above-mentioned spatial-temporal models, most of them are based on traditional GIS, which is difficult to realize the integration of space and time. Because of the separation of time and space of the traditional model, the spatial-temporal relationship of the data is also separated. So the spatial-temporal connotation is simple, which cannot map the temporal and spatial functions of RS objects and their relationship, and it is difficult to map the occurrence, growth, and extinction of RS ground objects. Cellular automata provide a framework for spatial-temporal modeling of RS data. Cellular automata is a kind of grid dynamic model with local spatial interaction and temporal causality in the discrete spatiotemporal state, which has the ability to simulate the dynamic spatiotemporal evolution process of a complex system. It can simulate the very complex system processes and phenomena of observed objects. Cellular automata have great flexibility and openness and have a broad application prospect in the spatial-temporal evolution relationship modeling of observation objects in RS. Cellular automata have unique advantages in modeling pollution systems with hydrodynamic characteristics [24]–[28].

C. Intelligent Computing Model and Data Mining Theory of RS-STBD

Intelligent computing and automatic analysis are the premise of RS-STBD for data mining, information extraction, and knowledge transformation from RS observation data. The processing of RS data has experienced three development stages from qualitative RS to quantitative RS [29], and then to intelligent RS [30]. Generally, the qualitative model and conceptual model are used to realize the qualitative analysis of RS. Using mathematical model, physical model, chemical model, and biological model, the quantitative inversion model is constructed to realize the quantitative measurement of RS. Intelligent computing model and spatial-temporal semantic model are used to analyze and calculate the semantic information of RS so as to realize the semantic representation, semantic extraction, semantic retrieval, and semantic understanding of intelligent RS spatial-temporal information. With the development of machine learning, intelligent computing of RS will become the core technology and mainstream algorithm of RS information extraction.

Intelligent computing of RS-STBD involves information extraction theories such as target detection [31] and image segmentation [32], target classification and recognition [33], target location [34], path tracking [35], path prediction, target information extraction [36], information fusion [37], information retrieval [38], and other information extraction theories. The spatial-temporal analysis aims to quantitatively analyze and mine spatial-temporal semantic relations and patterns of RS-STBD, including observation objects by means of machine learning, artificial intelligence, and mathematical statistics and analysis. This is a special spatial-temporal function of RS-STBD, which is different from the general image processing system. For the analysis and mining of RS-STBD, the main methods and theories include spatial-temporal classification [39], spatial-temporal clustering [40], spatial-temporal anomaly [41], change detection [42], spatial-temporal correlation analysis [43], spatial-temporal evolution analysis [44], spatial-temporal prediction [19], and other analysis and data mining methods of spatial-temporal information.

D. Workflow Theory of RS Computing

Workflow originates from the field of production organization and office automation. It mainly defines the concept of business process activities in the work. Its purpose is to decompose the work into well-defined tasks or roles, implement, and monitor these tasks according to certain principles and processes, so as to improve efficiency, control process, improve customer service, enhance effective process management, and other business purposes. Workflow is the core technology of business process automation. It constructs a workflow model or process model by analyzing the business process. The representation of the theoretical model of workflow generally adopts description language [45], object model, rule-based method, and graph or net-based method, such as directed graph [46], conditional directed graph, and Petri net [47].

According to the application fields of workflow, it is generally divided into Business WorkFlow (BWF) and Scientific WorkFlow (SWF) [48], [49]. BWF focuses on the automation of the business process, which can further be divided into process workflow, project workflow, and case workflow. RS computing is data-centric, which mostly involves the processing, sharing, and transmission task of high-throughput data. RS data processing and computing have a distinct pipeline processing nature, and the process of RS-STBD calculation and processing can be described systematically by SWF theory [50]. In other words, the different algorithms in the RS processing process are organized together, and the logical rule of the sequence mode, branch mode, and repetition mode is used to represent and implement RS computing.

III. RS Algorithm and Cloud Computing Technology

A. Types and Characteristics of RS Algorithms

RS algorithm has the characteristics of strong professionalism, involving many industries, and large data scale. RS algorithm has a distinct hierarchy and parallelism, which belongs to the computational intensive algorithm. According to the processing sequence, processing object, and algorithm idea, the RS algorithm can be divided into remote sensing data processing algorithm (RS-DPA), remote sensing information extraction algorithm (RS-IEA), and remote sensing application processing algorithm (RS-APA).

RS-DPAs include radiometric correction [51], registration [52], [53], terrain correction [54], [55], geometric calibration [56], [57], atmospheric correction [58], and other RS preprocessing algorithms; and it also includes image processing algorithms such as image filtering, image enhancement [59], mosaic [60], cutting, uniform color, fusion [61], [62], and other image processing methods. The preprocessing of RS data has strong pertinence, the processing process and parameters are very complex and diverse, and the sensor data formats of various satellites are not the same, which often brings great trouble to the design of its universal system.

RS-IEA is the core algorithm of RS data inversion. According to RS observation objects, it can also be divided into land RS inversion algorithm [63], [64], atmospheric RS inversion algorithm [65], and water RS inversion algorithm [66]. RS-IEA is also the main function of the RS application system. RS-IEA includes image segmentation [67], spectral-based classification [68], scene classification, and other pixel-based image processing methods, as well as target detection [31], target change and tracking [69], target classification, target recognition [33], and other target-based information extraction algorithms.

RS-APA is an important data source of various industry business systems based on RS application. According to different RS industries, RS-APAs are generally divided into thematic maps production methods applied in agriculture, forestry, surveying, mapping, meteorology, water conservancy, ocean, national defense, energy, transportation, geology, earthquake, health, engineering, statistical planning, ecological environment protection, disaster monitoring, land, resources exploration, and other industries. Moreover, different industries have different requirements for the accuracy and speed of the RS-APAs.

B. Workflow Customization and Control Technology of RS

In view of the complex RS business services and industry application requirements, it is necessary to reasonably configure the RS product production process of different businesses and realize intelligent RS algorithm customization and processing flow control. Considering the hierarchy and modularity of RS data processing, SWF technology well adapted for carrying out dynamic and intelligent process assembly, automatic task scheduling, and autonomous task control.

RS workflow technology involves the definition, assembly, and visualization of workflow, the management, and scheduling of workflow tasks. The definition, organization, mapping, and execution environment of workflow generally use eXtensible Markup Language (XML) or JavaScript Object Notation (JSON) to describe each serial and parallel processing flow. The hierarchical workflow based on the directed acyclic graph is constructed by using various workflow control structures such as conditional execution, iteration and repetition, and user-defined functions [70]. The computing task of RS can process the data in blocks and decompose the tasks, which is the theoretical basis of parallel processing of RS images. The essence of RS computing based on workflow is a kind of hierarchical and orderly collaborative computing of multimachines and multitasks.

C. RS Cloud Computing and Cloud Service Technology

As an interdisciplinary science and technology, RS computing has strong professionalism. In order to realize the cross-industry sharing of RS data services and computing services, it is highly necessary to encapsulate RS data and RS computing into RS services, and use cloud computing and cloud services to build RS cloud so as to realize the resources sharing of RS data and RS computing. Generally, RS cloud provides four levels of RS cloud computing services [71]: RS infrastructure service, RS platform service, RS data service, and RS software computing service (see Fig. 1). The essence of RS cloud computing is to provide a service technology through an Internet platform.

In order to realize the computing services and data distribution services of RS cloud, according to the current development of information technology and cloud computing, RS cloud service can be implemented by remote procedure call (RPC) [72], web application programming interface (Web API) [73], Java remote method invocation (RMI) [74], windows communication foundation (WCF) [75], and web service technology (WST) [76].

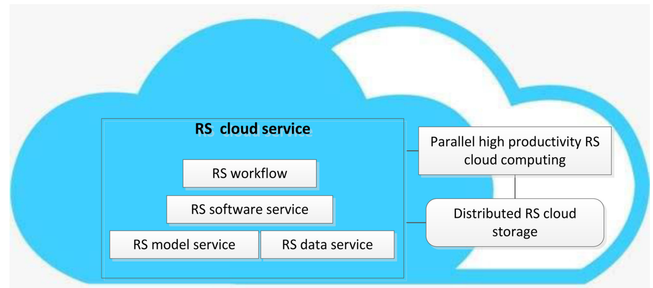

Fig. 1. Diagrammatic sketch of RS cloud storage, RS cloud computing, and RS cloud services.

1) RPC technology adopts the client/server mode to call remote computer program process through the network to realize remote request and service [77]. Different from local procedure call, which uses task-shared memory, it can synchronize tasks and send information to each other for conversation in a multitasking operating system. RPC runs in the distributed operating system, constructs the software environment of distributed RS computing, and realizes the communication between remote processes. RS service calls based on RPC protocol can be divided into synchronous calls and asynchronous calls. RS data sharing and RS computing service are realized by using the RPC interface. In essence, Web API, RMI, WCF, and WST are special cases of RPC.
2) Web API is a microservice architecture technology, which realizes web applications based on intelligent process services, such as storage services, message services, information services, search services, computing services [78]. Web API represents and provides access services, which can build RS services for various clients. We use HTTP verbs, such as get, post, put, and delete, and web API to implement create, retrieve, update, and delete operations of distribution service, and solve the function of adding, deleting, modifying, and searching remote information. Web API uses a web server, application server, database server, and storage and communication components to provide loosely coupled, autonomous, and decentralized RS services.
3) RMI technology uses a set of Java application programming interfaces of RPC to realize the development of distributed applications [79]. RMI uses a Java language interface to define remote objects. It combines Java serialization and RMP Protocol. It can make objects in one Java virtual machine (JVM) call methods of objects in another JVM. The distributed RS application constructed by RMI has the characteristics of transparent call, distributed garbage collection, and convenient access to stream. RMI is composed of a stub/skeleton layer, remote reference layer, and transport layer to provide distributed RS service system. RMI starts a stub and skeleton process in each of the two JVMs. The two processes transfer parameters and return values through socket communication to solve the call problem between different RS JVMs.

4) WCF technology is a series of application frameworks supporting data communication developed by Microsoft. It sends and receives messages between customers and services through processes or different systems, using the Intranet or Internet [80]. WCF integrates the functions of Web services, .Net remoting, message queuing, and enterprise services, and can be used for the development of RS service-oriented distributed applications. WCF can define the protocol of RS network service, the protocol of business service, the declaration of data type, and the related information of transmission security. In WCF architecture, a contract is used to define the parameters, messages, and service methods of the RS data service message system. WCF supports HTTP, TCP, named pipe, Microsoft message queue, and peer-to-peer TCP protocols. WCF uses endpoints to send or receive messages (or do both).
5) WST is a kind of remote calling technology that uses HTTP protocol to transfer data between client and server to realize cross-programming language and cross-operating system platform [81], [82]. WST is a self-describing and self-contained available network module. Its essence is to call the resources of other websites through a remote network. WST contains the standard protocol for communication between RS applications. The RS system functions provided by web services include security, distributed transaction coordination, and reliable communication. WST follows SOAP Protocol, encapsulates RS data by XML, and transmits RS data by HTTP protocol. SOAP uses XML message to call a remote method, WST interacts with the remote machine through the post and get methods of the HTTP protocol, and uses UDDI, WSDL, XML, SOAP technology to realize RS service discovery. WST can realize web-based RS applications with platform-independent, low coupling, self-contained, programs. WST also uses the open XML standard to describe, publish, discover, coordinate and configure RS network applications, and develop a distributed and interoperable RS application system.

The above five technologies have their own advantages and disadvantages. In the design of a cloud computing platform to achieve cloud services, we need to choose according to business needs. RPC supports cross-language services, while RMI only supports Java language. WST transfers XML text files over HTTP protocol, which is independent of language and platform. WCF is not an open-source, but can be called across platforms, and can only be deployed in applications, IIS, or Windows services. Web API is an open-source framework supporting mobile applications on .Net platform.

The mainstream technical solution of cloud computing is to reasonably select the above programming technologies and to realize cloud services of public cloud and private cloud by using core technologies such as distributed computing, parallel computing, utility computing, network storage technologies, virtualization, load balance, and content delivery network. Generally, large enterprises tend to set up business private cloud and provide a public cloud for external services, such as Google cloud, VMware cloud, Microsoft Azure, Amazon Web services (AWS), Tencent cloud, Huawei cloud, and Alibaba cloud.

D. Technical Specification of RS Cloud Service

The input–process–output specification of RS-STBD cloud service based on cloud computing is described as follows.

1)Service Description: Service name, service function, service parameters, and types, return results, and types.
2)Service Name: XXX_Service
3)Technology: WCF || RMI || RPC || Web API…
4)Input: Data 1; Data 2;…; Data M; Parameter 1; Parameter 2;…; Parameters N; Method.
5)Process:
Step 1: Product = Method (Data, Parameters);
Step 2: Information = Process (Product, Parameters);
Step 3: Provide Services;
… …
Step N: Provide Services;
5)Output: Product 1; Product 2;…; Product K; Information.

For the complicated structure of input parameters or return information, it is generally recommended to using structured format XML or JSON to encapsulate the input parameters or return information describing RS services.

IV. Architecture of RS Application and the Development of Complex System Engineering

A. System Architecture Design of RS Software

According to the functional requirements of RS data processing, RS information extraction, and RS product distribution, the design of RS software system architecture should make tradeoffs in processing performance, stability, rationality, and convenience. In order to facilitate the system development and maintenance of software engineering, the architecture design of the RS software system needs to meet the SOLID principle of object-oriented programming, namely single responsibility principle, open–closed principle, Liskov substitution principle, law of Demeter, interface segregation principle, dependence inversion principle [83]. As given in Table II, the popular software system architectures of RS at present mainly include layered architecture, event-driven architecture [84], microkernel architecture [85], and microservice architecture [86].

Here, the layered architecture is a general framework that meets the SOLID principle. The event-driven architecture is a popular distributed asynchronous framework pattern for creating scalable RS applications. The microkernel architecture is a framework derived from the operating system design, also known as a plug-in architecture pattern. The ideal system architecture is composed of a core system and plug-in module. The core system, also known as microkernel, usually contains minimal RS business logic and ensures that plug-ins required for RS applications can be loaded, unloaded, and running. Microservice architecture is also a service-oriented architecture [87]. Its RS service is fine-grained and its protocol is lightweight. The core of the microservice architecture is separate deployable units and RS service component, which contains RS business logic and processing flow. Separate deployable units are highly scalable, easy to deploy and deliver; RS service components are decoupled, distributed, independent from each other, and can be accessed using known protocols.

B. High-Efficiency Product Production Framework of RS Intelligent Processing

It is a complex system engineering to realize highly efficient RS intelligent computing. RS intelligent computing has the characteristics of data storage distribution, algorithm processing parallelism, and swarm intelligence coordination. Considering the industry demands characteristics of RS-STBD, parallel computing and intelligent computing must be considered in the design of the RS system architecture to achieve high-efficiency product production. RS parallel system can be designed in three forms: temporal parallelism (time overlap and pipeline time-division multiplexing), spatial parallelism (resource duplication and multidevice or multiprocessor), and spatial-temporal parallelism (time overlap and resource repetition) [88].

From the point of view of program and algorithm design of software engineering, RS-STBD parallel processing is divided into data parallelism and task parallelism. Data parallelism resolves a big data processing task into several subtasks with the same function, and each subtask processes different data at the same time. Task parallelism, also known as function parallelism or control parallelism, can further be divided into processes parallelism, thread parallelism, and instruction parallelism according to the granularity of task parallelism. High-performance computing of RS cloud platform generally adopts multicomputer cluster (such as Hadoop [89] and MapReduce [90]), multiprocess parallelism (such as MPI [91] and Spark [92]), multicore or multithread parallelism (such as OpenMP [93]), heterogeneous parallelism (such as GPU [94]), and other parallel processing technologies.

The key to improve the precision of intelligent processing is the design of intelligent processing models and algorithms for RS-STBD. The main problem is that intelligent processing algorithms are often dedicated and poor in generality. It is urgent to develop a general intelligent model and theory for RS intelligent information extraction.

C. Design Model of RS Cloud Computing

Cloud computing provides available, convenient, and on-demand network resources, computing resources, storage resources, software resources, and other network resource sharing services [95]. It includes various applications based on network services, software, and hardware facilities that provide these services in the data center. Cloud computing system has the advantages of supporting virtualization, quality of service, reliability, and scalability. For the research of distributed RS cloud computing system architecture, it is necessary to study the development mode, computing model, service model [96], and RS data management. The application and development of RS cloud computing need to consider the system availability, data management, design and implementation, message processing, management and monitoring, performance and scalability, flexibility, security, and other complex system problems. For these key problems of RS cloud computing, we can solve them according to different development modes and design logic. The literature [97] provides sharing, scaling, and elasticity patterns; reliability, resiliency, and recovery patterns; data management and storage device patterns; virtual server and hypervisor connectivity and management patterns; monitoring, provisioning, and administration patterns; cloud service and storage security patterns; network security, identity, and access management and trust assurance patterns; and common compound patterns. There are more than 100 cloud computing design patterns of eight categories. The document [98] provides 24 common design patterns of Microsoft cloud computing (see Table VII). The development of RS cloud computing needs to choose different design patterns reasonably according to the unique business requirements.

At present, the research on high-performance intelligent processing of RS-STBD in RS cloud service mostly focuses on the preprocessing algorithm, but relatively less on the post-processing. In RS cloud computing, parallel processing algorithms are often dedicated. The algorithms of different satellite data are very different and cannot be used universally. With the increase of data scale, the performance of cloud services tends to decline rapidly. The key to improve the intelligent processing performance of RS-STBD is the architecture design of the parallel system.

D. Development of RS Application System

The engineering business of the RS application system involves land, planning, agriculture, forestry, water conservancy, environmental protection, emergency relief, surveying and mapping, and military applications. RS can provide comprehensive and high-level surveying and mapping data acquisition and geographic information services for various industries. The mission of HREOS includes the observation of the earth's atmosphere, hydrosphere, lithosphere, and ecosphere, and can also be summarized as the observation of the atmosphere, water, and land. Among them, the observation of the atmosphere, water, and land involves the monitoring of the environment and disaster. The typical system engineering of HREOS is generally composed of satellite system, launch vehicle system, launch site system, measurement and control system, ground system, and application system, which constitute a set of complex information system.

As shown in Fig. 2, HREOS can roughly be divided into three systems: satellite system, ground system, and application system. According to the level of processing function, the application system is divided into RS basic platform, RS preprocessing system, RS information extraction system (such as measurement, analysis, segmentation, classification, and evaluation), GIS, RS, and GPS information fusion, and industry application system (such as smart city and city brain). Among them, the RS data acquisition system uses the detection carrier wave (such as infrared, visible, ultraviolet, electromagnetic, sound, and gravity) to generate RS data. The RS data retrieval system processes the RS data to extract the RS information on the ground objects, and further uses the RS information application system to process and form knowledge and thematic products.

At present, mainstream business platforms of RS image processing software are ERDAS image, environment for visualizing images (ENVI), and PCI Geomatica (see Table VIII). In addition, there are ESA Digital Twin Earth and other software. In the RS cloud platform, as shown in Fig. 3, the systems that support cloud data management and provide data as a service (DaaS) include Google's Hadoop distributed file system (HDFS), AWS, data cube of Amazon, digital globe's geospatial big data platform (GBDX), data and information access services (DIAS), etc.; the

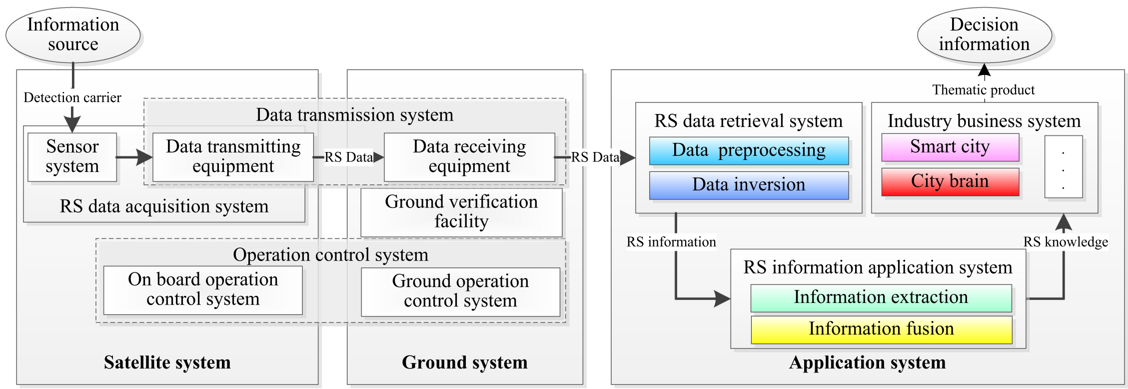

Fig. 2. HREOS architecture.

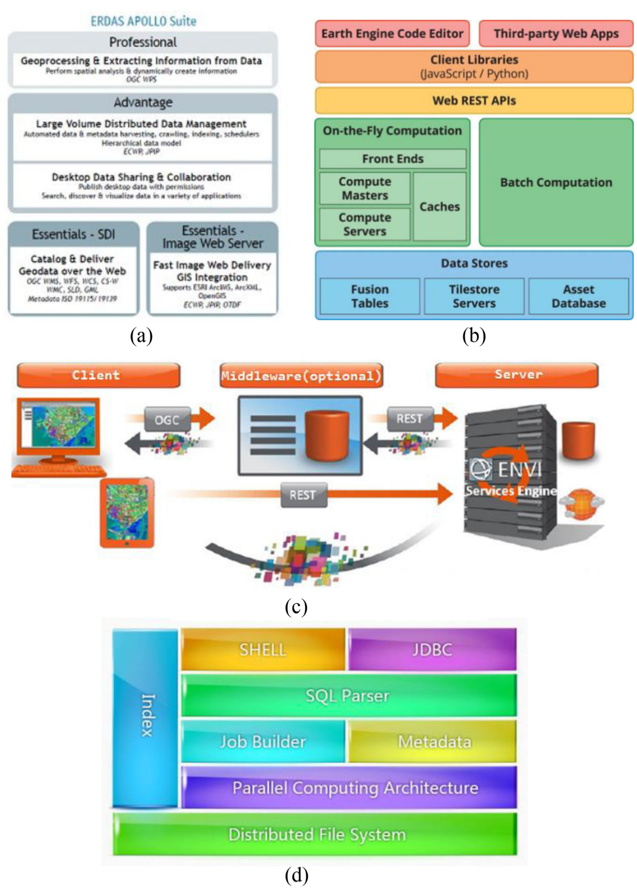

Fig. 3. GEE, ESE, ERDAS Apollo, and Data Cube system architecture. (a) ERDAS Apollo. (b) GEE. (c) ENVI services engine. (d) Data cube.

systems that support online data processing and analysis and provide software as a service (SaaS) include ArcGIS online and NASA EOSDIS. Among them, the cloud computing platforms corresponding to Google Earth Engine (GEE) [99], [100], data cube, ENVI Services Engine (ESE), and ERDAS Apollo can provide both DaaS and SaaS service modes.

The development of the RS application system can adopt waterfall development, iterative development, spiral development, agile development, and other software engineering development model. For the rapid development of the RS application system, the secondary development is usually based on the API or SDK provided by the RS image processing platform. For example, ENVI's interactive data language, GEE RS cloud platform, ERDAS imagine spatial modeler and C Developer's toolkit, and PCI Geomatica's software toolkit with geomatics generic database technology can realize the rapid development of RS application system.

V. Problems and Solutions

1) Data representation and storage of RS-STBD: Due to the particularity of the development of RS, the research of RS engineering and technology in various countries is relatively independent. As a result, the sensor parameters of different satellite systems are complex and diverse, and all kinds of RS data and metadata are not universal, which brings great difficulties to the sharing and processing of RS data. It is an important problem of RS-STBD to establish a public data format and data exchange standard for different satellite systems. In addition, according to the characteristics of RS data, constructing a multilevel and distributed storage structure suitable for efficient processing, rapid display, and intelligent information extraction of RS data is also a very noteworthy issue in RS-STBD research.
2) The research of the RS-STBD processing model: The emphasis on the RS-STBD processing model is to realize the application and construction of EOS, and also to be compatible with the construction requirements of GIS and GPS. However, the existing RS-STBD models have basically improved data models based on the TGIS model. At present, it is urgent to establish an RS-STBD model that can map the complex spatial-temporal changes of ground features, meet the high-performance image processing, and easy to realize the intelligent processing of RS data.
3) The algorithm designs of RS-STBD: The RS algorithm has strong pertinence. How to build a common algorithm is the bottleneck of the development and application of RS information technology. It is the key to the popularization and application of RS-STBD to study the RS algorithm and process flow, and establish a generally shared RS algorithm. In particular, RS brain and mind-inspired computing technology is a prospective problem of RS-STBD

intelligent information extraction. This technology uses intelligent perception and cognition to simulate visual interpretation and image interpretation and can achieve tasks such as RS scene classification, target detection, target classification, and target recognition.

At present, deep learning has made great progress in the application of RS, especially in the perceptual information extraction of high-resolution RS images. However, due to the poor interpretability of deep learning, it is impossible to analyze the cognitive mechanism of ground objects. In order to realize the real intelligent RS system, we need to process both information perception and information cognition. RS brain and mind-inspired computing for RS-STBD will provide strong theoretical and technical support.

4) EOS construction for RS-STBD: The construction of EOS is a complex system problem. It involves a lot of professional knowledge, science, and technology, which needs the cooperation and joint development of all walks of life. The application system design of EOS must consider the uncertainty, sparsity, incompleteness, and imbalance of RS data, the complexity, nonlinearity, and dynamic evolution of RS algorithms, the diversity and hierarchy of RS applications, and the integrity, openness, and self-organization of the RS system. Only by making full use of high-performance computing, cloud computing, and artificial intelligence technologies can we effectively build a practical application system of HREOS.

VI. Conclusion and Prospect

The research on models, algorithms, and systems for RS-STBD processing involves complex scientific problems, technical bottlenecks, and inconstant requirements of engineering applications. This article summarizes the data types and processing theoretical models of RS-STBD, the high-performance algorithm design based on cloud computing, and the architecture design and engineering development methods of complex RS applications. Finally, the existing problems of current research are analyzed, and the relevant solutions are given.

We believe that with the development of scientific exploration, technical research, and application development of RS-STBD, RS satellites will tend to be miniaturized in the future, and efficient data acquisition will be realized through the networking of unmanned autonomous smart satellites constellation. In the future, intelligent RS satellite systems would become the mainstream system; "AI+RS" would provide more efficient information extraction algorithms and application system solutions.

Appendix A

TABLE III
EOS Satellite Parameters and RS Data of America

Nation & Operator	Satellite Designation & Application	Band & Beam mode	Resolution (m)	Swath Width (km)	Revisit Time (day)
U.S. DigitalGlobe, Inc.	Ikonos-2	Panchromatic Multispectral	1 4	11.3	1-3
	Orbiew-1,2,3	Panchromatic Multispectral	1 4	8	3
	GeoEye -1/Orbiew-5	Panchromatic Multispectral	1 4	11.3	3
	Quickbird-2	Panchromatic Multispectral	0.61-0.72 2.44-2.88	16.5	1-6
	Wordview-1	Panchromatic	0.61	14-110	1.7
	Wordview-2	Panchromatic Multispectral	0.5 1.8	16.4-110	1.1
U.S. EOS Landsat series satellites of NASA/USGS	Landsat-5,7,8	Panchromatic Visible light Near IR Thermal infrared SWIR	15 30 30 100 30	185	16
U.S. EOS satellites	Terra(EOS/AM-1)	TERRA-MODIS TERRA-MISR TERRA-ASTER	250,500,1000	2330 360 60	1
	Aqua(EOS/PM-1)	AQUA-MODIS CERES AIRS AMSU-A,HSB,AMSR-E	250,500,1000	2330 20 1650	1
	Aura (EOS/Chem-1)	OMI,HIRDLS,MLS,TES			
Planet, Inc., U.S.	RapidEye constellation of five satellites	Visible light, Red edge, Near IR	5	77	1
Radarsat Constellation Mission of Canada Space Agency (CSA)	Radarsat C-band SAR satellites (Radarsat-1,2)	Standard Mode Spotlight Mode Ulra-Fine Mode Multi-Look Fine Mode Wide Mode ScanSAR Narrow Mode ScanSAR Wide Mode	30 1 3 8 30 50 100	100 18 20 50 150 300 500	Programmable

TABLE IV
EOS SATELLITE PARAMETERS AND RS DATA OF EUROPE

Nation & Operator	**Satellite Designation & Application**	**Band & Beam mode**	**Resolution (m)**	**Swath Width(km)**	**Revisit Time(day)**
Global Monitoring for Environment and Security (GMES) of ESA/EU	Sentinel C-band SAR satellites (Sentinel-1A,1B)	Wave mode(WV) Stripmap mode(SM) Extra Wide Swath(EW) Interferometric Wide Swath mode (IW)	5×5 5×5 20×40 5×20	20 80 400 250	6
	Sentinel optical satellites (Sentinel-2A,2B)	Visible Near IR SWIR	10 20 60	290	5
	Sentinel sea satellites (Sentinel-3A,3B,3C,3D)	Optics, SAR			4
	Sentinel atmosphere satellites (Sentinel-5P)	TROPOMI			
European Remote Sensing (ERS) satellites of ESA	C-band ASAR ENVISAT satellites (ERS-1,2)	Wave mode Image mode Wide swath mode Global monitoring Alternating polarisation	5 30 150 1000 30	5 100 400 400 100	35
SPOT (Satellites Pour l'Observation de la Terre or Earth-observing Satellites) satellites constellation of France	SPOT-1,3,4 SPOT-5 SPOT-6	Panchromatic Multispectral Panchromatic Multispectral Panchromatic Multispectral	10 20 2.5/510 1.5 1.5 6	60	26
	Pléiade satellites (Pleiades-1,2)	Panchromatic Multispectral	0.5 2	20	26
EOS of Italian Space Agency (ASI) and Italian Ministry of Defence (MoD)	COnstellation of small Satellites for Mediterranean basin Observation (COSMO-SkyMed) High-resolution X-band SAR satellites	Spotlight mode Stripmap mode SanSAR mode	1 3,15 30,100	10 40,30 100,200	
TerraSAR-X satellites of German Aerospace Center (DLR) and EADS Astrium GmbH	X-band land SAR satellites (TerraSAR-X/TanDEM-X)	Spotlight mode Stripmap mode ScanSAR mode	1 3 16	5,10 30 100	4.5
Surrey Satellite Technology Ltd., UK	UK-DMC-2 (United Kingdom - Disaster Monitoring Constellation-2)	Panchromatic Multispectral	4 32		
Deimos Space, Inc., Spain	Deimos-1 Deimos-2	Visible light Panchromatic Multispectral	22 0.75 3	650 12,24 12,24	3 1 1
Horizon(Ofeq) spy satellite family of Israel	Ofeq-7,8,9	Visible light,SAR	<0.5		
EROS (Earth Resources Observation Systems) satellite family of Israel	EROS-A EROS-B	Standard Panchromatic Panchromatic Strip	1.9 1.1-1.5 0.7 0.7	14 9 7 7×14	5
EOS Mission Constellation of Russian	Resurs-P3	Panchromatic Multispectral Hyperspectral	1 4 25-30	38	3
	Resurs-DK	Panchromatic Multispectral	0.9-1.7 2-3	28.3,40	5

TABLE V
EOS SATELLITE PARAMETERS AND RS DATA OF ASIA

Nation & Operator	**Satellite Designation& Application**	**Band & Beam mode**	**Resolution (m)**	**Swath Width(km)**	**Revisit Time(day)**
Japan Aerospace Exploration Agency (JAXA)	Marine Observing Satellite (MOS-1)	VNIR Thermal infrared Microwave	50 900 23000	100 1500 317	
	Japanese Earth Resources Satellite (JERS-1)	Optics,SAR			
	Advanced Land Observing Satellite (ALOS,2,3)	Multispectral Stereoscopic SAR high-resolution SAR wide-area SAR spotlight	2.5 10 3 100 1×3	70 70 50-70 350 25	2
Indian resource satellite series	Resourcesat-1(IRS-P6)	Multispectral LISS-4 Multispectral LISS-3 wide-angle AwiFS	5.8 23.5 56	23.9 141 740	5,23
Indian mapping satellite series	Cartosat-1/2 (IRS-P5) panchromatic stereo imaging satellite	Forward looking Backward looking	2.452 2.187	29.42 26.24	5
South Korea	Arirang satellites(KOMPSAT-1,2)	Panchromatic Multispectral	1 4	15	3
Earth observation mission of Thailand	Thailand earth observation satellites (Theos)	Panchromatic Multispectral	2 15	90	26

TABLE VI
EOS SATELLITE PARAMETERS AND RS DATA OF CHINA

Nation & Operator	**Satellite Designation& Application**	**Band & Beam mode**	**Resolution(m)**	**Swath Width(km)**	**Revisit Time(day)**
China land observation satellite series	Huanjing-1A (HJ-1A)	Multispectral Hyperspectral (110-128 bands)	30 100	360 50	4
	Huanjing-1B (HJ-1B)	Multispectral IR	30 150,300	360 720	4
	Huanjing-1C (HJ-1C) S-band SAR satellite	Band mode Scanning mode	5 20	40 100	4
	Ziyuan-1 01/02 (CBERS-01,02)	Multispectral IR	20 78	113 119.5	3 26
	Ziyuan-1 02B(CBERS-02B)	Panchromatic Multispectral	2.36 5,10	27 60	3
	Ziyuan-1 02C(ZY-1 02C)	Panchromatic Multispectral IR	2.36 20 258	27 113 890	3
	Ziyuan-1 04(CBERS-04)	Panchromatic Multispectral IR	5,10 20 40,80	60 120 120	3 26 26
	Ziyuan-3(ZY-3) stereo mapping optical satellite	Forward looking Backward looking Downward looking Multispectral	3.5 3.5 2.1 6	52 52 51 51	5
	Ziyuan-3 02(ZY-3 02) stereo mapping optical satellite	Forward looking Backward looking Downward looking Multispectral	2.5 2.5 2.1 5.8	51	3
China High-resolution Earth Observation System (CHEOS)	Gaofeng-1 (GF-1) high-resolution optical satellite	Panchromatic Multispectral	2 8,16	60 800	4 2
	Gaofeng-2 (GF-2) high-resolution optical satellite	Panchromatic Multispectral	1 4	45	5
	Gaofeng-3(GF-3) multi-polarized C-band SAR satellite	Spotlight mode(SL) Strip imaging mode Scan imaging mode Wave imaging(WAV)	1 3-25 50-500 10	10 30-130 300-650 5	Mono-look<3, dual-look <1.5
	Gaofeng-4 (GF-4) staring synchronous satellite	VNIR MWIR	50 400	400	20s
	Gaofeng-5 (GF-5) hyperspectral observation satellite	Hyperspectral(330bands) Full-spectrum (12 bands)	30 40	60	51
	Gaofeng-6(GF-6) agricultural red edge satellite	Panchromatic Multispectral Wide Multispectral	2 8 16	90 90 800	4
	Gaofeng-7 (GF-7) panchromatic stereo imaging satellite	Panchromatic Multispectral	0.8 3.2	20	
China Ocean Observation Satellite Series	Haiyang-1A/1B (HY-1A/1B) ocean resources satellites	COCTS Coastal Zone Imager(CZI)	1100 250	1400 500	1 7
	Haiyang-1C/1D (HY-1C/1D) ocean resources satellites	OCTS CZI Ultraviolet Imager	1100 50 550	2900 950 2900	1 3 1
Beijing-1 small satellite constellation of 21AT Co. Ltd.	Beijing-1(BJ-1)	Panchromatic Multispectral	4 32	24 600	
	Beijing-2(BJ-2)	Panchromatic Multispectral	0.8 3.2		1-2 1-2
Jilin-1 small satellite constellation of CGSTL Co. Ltd.	Jilin-1(JL-1A) optical satellite	Panchromatic Multispectral	0.72 2.88	11.6	3.3
	Jilin-1 staring video satellite	staring video	1	19	120s-3.3d
	Jilin-1 02A, 02B (JL-1 02A/02B) high-resolution satellite	Panchromatic Multispectral	0.75 3	21.5	0.25
	Jilin-1 01 / 02 (JL-1 01/02)hyperspectral satellite	PMS(19 bands) SWIR(4 bands) MWIR(1 band) LWIR(1 band)	5-20 100 100 150	58.7 64 64 96	
Zhuhai-1 small satellite constellation of Orbita Co. Ltd.	OVS Video Satellites OHS Hyperspectral satellites OSS SAR Satellites OIS Infrared Satellites OUS high-resolution optical satellites	Video Hyperspectral(32 bands) SAR IR Optical	0.9 10	4.5 500	25fps 2
SuperView-1 small satellite constellation of Siwei Co. Ltd.	SuperView-1,2	Panchromatic Multispectral	0.5 2	12	

APPENDIX B

TABLE VII
MICROSOFT'S 24 DESIGN PATTERNS FOR RS CLOUD COMPUTING

Design Patterns	**Function & Characteristic**	**Design Patterns**	**Function & Characteristic**
Cache-Aside Pattern	According to the demand, load RS data from data storage cache to improve system performance and maintain data consistency	Leader Election Pattern	Ensure that task instances do not conflict with each other, resulting in contention for shared RS resources
Circuit Breaker Pattern	Improve RS application stability and flexibility[102]	Materialized View Pattern	Support efficient query and extraction of RS data, improve the performance of the application
Compensating Transaction Pattern	Cloud hosted RS applications for complex business processes and workflows	Pipes and Filters Pattern	Allows deployment and independent RS tasks to improve performance, scalability, and reusability
Competing Consumers Pattern	For multiple concurrent RS user processing	Priority Queue Pattern	Different RS service levels are provided for independent users
Compute Resource Consolidation Pattern	Improve the utilization of RS computing resources	Queue-Based Load Leveling Pattern	Queue buffer resource is used to ensure availability
Command and Query Responsibility Segregation	Improve the performance, scalability and security of RS system	Retry Pattern	Improve the stability of RS application
Event Sourcing Pattern	Improve RS system performance, scalability and responsiveness	Runtime Reconfiguration Pattern	Keep the availability of RS system and reduce down time
External Configuration Store Pattern	Used to share configuration information across RS applications and instances	Scheduler Agent Supervisor Pattern	In the distributed RS system, flexibility and flexibility are added, and the operations such as exception recovery and fault handling are added
Federated Identity Pattern	Reduce user management requirements and improve the user experience of RS applications	Sharding Pattern	Improve the expansibility of RS system
Gatekeeper Pattern Pattern	Provide a security layer to limit attacks on RS systems	Static Content Hosting Pattern	Reduce the need for potential high load RS computing instances
Health Endpoint Monitoring Pattern	Verify that RS application and RS service are executed correctly	Throttling Pattern	Implement load balancing to ensure that the RS service of system quota resource continues to run
Index Table Pattern	It can provide RS application with fast location and retrieval of RS data and improve query performance	Valet Key Pattern	RS storage system or queue application for cloud hosting to minimize cost, improve scalability and performance

APPENDIX C

TABLE VIII
MAINSTREAM RS DATA PROCESSING SOFTWARE AND SYSTEM

Software and Platform	**Developer**	**Functional Introduction**
ESE	Exelis Visual Information Solutions, Inc. U.S.	ENVI Services Engine(ESE) is the network service function of ENVI (environment for visualizing images), a large RS image processing platform. ESE is based on REST framework and can run in cluster environment. It provides Web services and RS cloud services for enterprise image processing, and has scalability and load balancing functions[103].
ERDAS Apollo	Intergraph, Inc. U.S.	ERDAS Apollo is the data sharing function of the mainstream RS image processing system ERDAS. Apollo provides spatial information infrastructure construction and geographic information sharing services, which can provide users with image data management, publishing, sharing and services. Apollo's spatial data architecture provides an interactive framework, supports the management and service of metadata and maps, and provides a secondary development package, which can build a spatial information system according to the application requirements and simplify the complex business workflow[104].
PCI Geomatica	PCI, Inc. Canada	PCI is a large software system integrating RS image processing, radar data analysis, GIS, spatial analysis, mapping and digital photogrammetry[105].
ECognition	Definiens Imaging, Inc. Germany	Provide object-oriented RS image analysis, management and application system, support the secondary development of multiple languages[106].
GEE	Google Inc. U.S.	Google Earth engine (GEE) is a cloud based spatial-temporal data analysis and computing platform for online real-time processing of satellite earth observation RS images. GEE uses Hadoop Distributed File System (HDFS) storage massive RS data resources in the cloud, which can publicly access, call and analyze[100].
GBDX	DigitalGlobe Inc. U.S.	Using Amazon Web Services (AWS) and Data Cube[107] to provide cloud based global RS image and computing resource service in Geospatial Big Data platform(GBDX)[108].
DIAS	ESA,EU	The Copernicus Data and Information Access Services (DIAS) of ESA is used to provide the data access service and software development tools of Sentinel series satellites[109].
EOSDIS	NASA, U.S.	The Earth Observing System Data and Information System (EOSDIS) is mainly responsible for NASA's geoscience data archive, product production and distribution cloud services[110].
ArcGIS online	ESRI Inc. U.S.	ArcGIS online is an online integration tool of GIS and RS for ESRI geospatial cloud. It uses interactive maps to connect RS data, geographic location and developers, and provides efficient and intelligent spatial-temporal information processing and analysis tools.
IRSA, CAESAR and HypEYE	RADI, CAS,China	IRSA is a general RS image processing system with cloud computing and FPGA field computing; CAESAR is a radar image processing system; HypEYE is a hyperspectral image processing and analysis system[10]
Titan Image	Aerospace TITAN, China	Titan Image is a RS image processing software with RS image processing, visualization, process customization, GIS function and secondary development function[111]
PIE	PIESAT Co., Ltd, China	PIE(pixel information expert) is a general RS image processing system. The system can realize the whole process closed-loop processing of optical, radar, hyperspectral and UAV data from acquisition, processing, analysis to service.
RSCloudMart	CHINARS Co. Ltd, China	RSCloudMart provides RS cloud service platform of high-resolution satellite RS data acquisition, data processing, product production, data analysis and processing, data distribution and other services.
Yuntu	CGSTL Co. Ltd, China	It provides RS data service and technical support based on network for RS application development, and has the ability of RS data mining, collection and sharing.

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