The Existing Remote Sensing Index Resources

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Remote sensing indices are widely used in various fields of geoscience research. However, there are limits to how effectively the knowledge of indices can be managed or analyzed. One of the main problems is the lack of ontology models and research on indices, which makes it difficult to acquire and update knowledge in this area.

Keywords: Remote sensing ; software ; remote sensing indices

1. Introduction

Remote sensing indices are used to characterize surface features or physical quantities. They are produced from mathematical operations on reflectance or radiance values in different spectral bands of remote sensing data. Remote sensing indices, such as vegetation indices [1], are applied in a wide range of fields, including forestry [2], soil [3][4], and water quality [5]. In recent years, there has been an increasing interest in developing remote sensing indices using multiple data sources and novel technologies [6][7][8][9].

Existing research recognizes the critical role of knowledge management and the utilization of models for scientific research [10]. However, much less is known about how to effectively manage and utilize indices [11]. Although some studies have developed indices repositories to integrate and manage indices, management of indices-related resources and knowledge remains insufficient. The major limitation of existing repositories is the lack of appropriate representation of indices.

Currently, emerging technologies, such as artificial intelligence, can assist scientists in managing and obtaining new knowledge from massive amounts of data and literature more effectively [12]. Knowledge graphs (KG) [13], a method for representing knowledge in terms of entities, attributes, and relationships, have gained increasing interest in recent years. In the field of remote sensing, KGs are primarily employed for extracting and organizing concepts from diverse and heterogeneous data sources [14], integrating and managing data resources [15], aiding tasks such as scene classification [16], and semantic segmentation [17] in remote sensing image interpretation [18]. By linking external heterogeneous information, KGs can also contribute to representation learning and ontology reasoning for crop identification [19], disaster prediction [20], oil spill detection [21], etc. To the best of our knowledge, however, there is no published KG for remote sensing indices. Existing KGs are unsatisfactory because they are not designed to represent remote sensing indices, and they are incapable of analyzing and managing the relationships and mathematical semantics among indices.

2. The Existing Remote Sensing Index Resources

To facilitate the selection and computation of remote sensing indices, various software tools and repositories offer abundant resources and functionalities (**Table 1**).

Table 1. A categorization for remote sensing indices resources.

Category	Typical Resources	Advantages	Disadvantages in Resources Management
Data products	**MODIS, Landsat, Sentinel, AVHRR, etc.**	(a) Data ready to use, no need for calculation (b) Various spatial and temporal scales	(a) Resources fragmentation (b) Lack of standardization and reference information

Category	Typical Resources	Advantages	Disadvantages in Resources Management
Platform software	**ArcGIS Pro 3.2 [22], ENVI 5.7 [23], etc.**	(a) Built-in index functions (b) Integrated with various processing and analysis tools	(a) Limited interoperability and expandability (b) Lack of index-related metadata
Cloud-based platform	**Google Earth Engine (GEE) [24]**	(a) Extensive related resources and a rich set of tools for index analysis (b) Computational capacity	(a) Steep learning curve (b) Limited interoperability and expandability
Specific index calculation tools	**ARTMO [25], ExtractEO [26], Remote Sensing Indices Derivation Tool [27]**	(a) Easy to use (b) Designed specifically for calculating indices	(a) Limited scope (b) Lack of integration (c) Limited standardization and documentation (d) Lack of index-related metadata
Index databases	**Index DataBase (IDB) [28]**	(a) Comprehensive collection of indices, includes information on sensor compatibility	(a) Outdated information (b) Limited searchability (c) Lack of expandability
Standardized catalog of indices	**Awesome Spectral Indices (ASI) [11]**	(a) Machine-readable format, easy to update (b) Connection to related resources	(a) Limited scope and searchability

As shown in **Table 1**, the common resources of remote sensing indices are divided into six categories. Researchers and users can directly use the data products of indices without the need for computation. Nevertheless, the variety of data products is caused by various data sources, developers, and domains. It also leads to the absence of data product standardization. In addition, the spectral information of sensors and their resolution vary depending on the field. Unfortunately, the calculation, formats, and application scenarios of indices lack unified specifications or reference information, which makes it challenging to fully understand data products for non-expert users. A possible solution is to develop a tool that can provide universal metadata for indices. Researchers or users would then be able to determine whether an index could be conducted with the necessary resolution or spectral information.

Platform software can help researchers calculate their own indices when existing data products do not meet their needs. Numerous index functions are implemented by well-known platform software such as ArcGIS [22] and ENVI [23] through their built-in band computation. However, only a few common indices are available on these platforms. Additionally, platform software does not offer enough relevant metadata to assist users in locating and comprehending the requirements of indices.

This issue has been partially resolved by cloud-based platforms by integrating big data storage and computing capacity. As the most prevalent cloud-based geospatial science platform, Google Earth Engine (GEE) [24] provides extensive remote sensing data and a rich set of tools for index analysis. It significantly reduces the barriers to entry for remote sensing research [29]. However, while platform software can calculate common indices, it is not keeping up with the rate at which index development grows. Furthermore, the indices in platform software are deficient in metadata and do not support knowledge management. While platform software provides certain APIs [30] to help with the creation of extension applications, each index in applications is based on their own specific implementation code. Therefore, support for certain and relatively recent sensor data and indices is typically limited in the platform software.

There are also several specially designed computational tools for calculating new indices. They could be complementary to platform software. For example, Rivera et al. [25] developed the Automated Radiative Transfer Models Operator (ARTMO) package. ARTMO is a spectral index evaluation tool based on MATLAB [31]. ExtractEO, developed by SERTIT (https://sertit.unistra.fr/, accessed on 22 August 2023), is a remote sensing index computation tool flow for reading optical and SAR satellite data [26]. It can load and overlay bands, clouds, DEM, and spectral indices in a sensor-independent manner. The Remote Sensing Indices Derivation Tool is an open-source program for calculating indices [27]. It processes data from various satellite sensors, enabling the calculation of multiple indices for vegetation, water bodies, etc. Since they were designed for particular data or indices, it is obvious that their functionality is limited and may not satisfy needs. Moreover, because they were created separately, there is a lack of interoperability between them. They frequently lack index-related metadata collection and management. As a result, it is difficult for users to understand the calculations, data formats, and research scenarios of indices.

Researchers will encounter difficulties when querying and analyzing indices due to the wide variety and dispersed distribution of resources. This issue has not been adequately addressed by the aforementioned tools. A tool that unifies the scattered data and information of indices is needed. The Index DataBase (IDB), developed in [28], is a professional database for satellite sensors and indices. It provides guidance information for indices applications [32]. IDB covers over 500 indices from various domains. Users can search for indices with keywords or the type of sensor and index on the IDB website.

However, the IDB’s most recent records only go back to 2011, which means they lag behind the developments in indices. Meanwhile, IDB lacks technologies to facilitate rapid data parsing and construction. These issues pose challenges for index updates. Recently, Montero et al. [11] introduced the “Awesome Spectral Indices” (ASI), a standardized catalog of spectral indices for earth science. ASI offers a rich index catalog that is machine-readable and linked to a Python library. Each ASI index comes with a long list of properties, including the name, formula, and source references. The user community has the flexibility to extend ASI.

In summary, common sources for multi-source information about indices are limited, apart from ASI and IDB. IDB and ASI lack a standard format and are built on specific environments and dependencies. The relationships between indices and concepts, as well as the semantic relationships between indices, are difficult to represent for all resources, particularly in the mathematical semantics of index formulas.

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