

## WEB SERVICES FOR BIG EARTH OBSERVATION DATA

*Serviços Web para Grandes Dados de Observação da Terra*

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### ABSTRACT

The aim of geospatial web services is to enable users to share and process geospatial data on the Web, no matter what platform or protocol is used. In this paper, we investigate what the design decisions needed to implement web services for big Earth observation (EO) data are. The focus of the work is discussing what is unique about big EO data and why current standards are unsuitable for big EO data analytics. Instead, simpler APIs can be more effective for accessing big EO data than generic services such as WMS and WCS, especially for data analytics. We support this viewpoint by describing the WTSS - Web Time Series Service - that offers time series of remote sensing data using a simple API and is suited for big data analytics.

**Keywords:** Web Services, Big Data, Geospatial Data.

### RESUMO

O objetivo dos serviços web geoespaciais é permitir que os seus usuários possam compartilhar e processar dados na Web, não importando qual plataforma ou protocolo seja usado. Nessa artigo nós investigamos quais são as decisões de projeto necessárias para implementar serviços web para grandes volumes de dados de observação da Terra. O foco do trabalho é a discussão das especificidades desse tipo de dado e o porquê dos padrões atuais não serem adequados. APIs mais simples podem ser mais efetivas para acessar esses grandes volumes de dados que serviços genéricos como WMS e WCS, especialmente quando se trata de processamento analítico. Nós reforçamos esse ponto de vista com a descrição do WTSS - Web Time Series Service, que oferece séries temporais de dados de sensoriamento remoto através de uma API simples mais adequada para a análise de grandes volumes de dados.

**Palavras chaves:** Serviços Web, *Big Data*, Dados Geoespaciais.

## 1. INTRODUCTION

Earth observation (EO) satellites produce vast amounts of geospatial data. As an example, the archive of medium-resolution Landsat satellite at the US Geological Survey holds more than five million images of the Earth's surface, with about 1 PB of data. Most space agencies have adopted an open data policy, making unprecedented amounts of satellite data available for research and operational use. This data deluge has brought about a major challenge for Geoinformatics research: *How to design and build technologies that allow the EO community to use big data sets?*

EO satellites provide a continuous and consistent set of information about the Earth's land and oceans. Using big EO data sets, we can detect long-term changes and trends in the environment, and measure the impacts of climate change, urban and ocean pollution and land expansion for food production. To transform data in information, we need to analyze terabytes of data, with different spectral, temporal, and spatial resolutions, acquired by different sensors and stored at different places. Given the broad application areas of EO data, researchers need to consider how to store and organize them in a way that will facilitate data interoperability and data analytics.

The issue of handling big geospatial data has attracted much attention in recent literature. Vitolo *et al.* (2015) reviewed the web technologies dealing with big environmental data, concluding that domain-specific projects often require tailored solutions. Li *et al.* (2016) revisited the existing geospatial data handling methods and theories to determine if they are still capable of handling emerging geospatial big data. They concluded that traditional data handling approaches and methods are inadequate and new developments are needed. However, their conclusions are focused on the processing of discrete geographical data, as data captured by mobile devices and GPS based sensors. Amirian *et al.* (2014) evaluated typical and modern database systems used for the management of big geospatial data, concluding that there is no single solution that meets all the user needs; therefore geospatial data handling is an open issue. Guo *et al.* (2014) presented

an on-demand computing schema for remote sensing images based on a processing chain model that runs on a private cloud computing platform. However, their motivation is on the processing of timestamps of imagery, not fully exploiting the processing of time series of data.

There also have been recent technological developments for handling big geospatial data. Alternatives include MapReduce based solutions such as Google Earth Engine (GORELICK, 2012), distributed multidimensional array databases such as SciDB (STONEBRAKER *et al.*, 2013) and object-relational DBMS extensions such as RasDaMan (BAUMANN *et al.*, 1998). Unlike the current state of object-relational databases for geospatial data, which have been standardized, each of these solutions is unique and incompatible with the others.

Given the incompatibility of the available architectures for big geospatial data, the question that naturally arises is whether we can still enjoy the benefits of interoperability provided by web services. Geospatial web services are important for interoperability, integration with applications and data sharing. In other words, *is it possible and viable to extend the current generation of geospatial web services to work with big geospatial data?*

To answer this question, we need to consider the standards proposed by the Open Geospatial Consortium (OGC). The OGC has played a crucial role in geospatial data interoperability by proposing web services standards for visualizing, disseminating and processing geospatial data. These include the Web Map Service (WMS), Web Coverage Service (WCS), Sensor Observation Service (SOS) and Web Processing Service (WPS) standards. Some space agencies have adopted some OGC web services to deliver their EO products. However, OGC standards have not yet proved to be a consensus solution when it comes to process the big EO data sets available in the agencies repositories, to extract information in a timely and robust way. In this paper, we investigate if the implicit decisions taken by OGC when designing services such as WMS, WCS and WFS allow them to be used for big EO data. We also consider whether new kinds of web services are required to handle big EO data efficiently.

In what follows we will argue that OGC services such as WMS, WFS and WPS rely

implicitly on a backend that stores EO data as a stack of 2D images. We consider that their design is inadequate for scientists working with large sets of remote sensing time series. We also describe a new proposal for a Web Time Series Services (WTSS), which is better suited for accessing large sets of EO time series. We illustrate WTSS by presenting some applications using it. We conclude by looking ahead at the improvements required in WMS and WCS for efficient support for big EO data retrieval and processing.

This paper is based on Vinhas *et al.* (2016), previously presented at GEOINFO conference (<http://www.geoinfo.info/>).

## 2. WHY CURRENT WEB COVERAGE SERVICES ARE NOT FIT FOR BIG DATA

When designing an architecture for big EO data, one needs to consider the needs of the users. Researchers typically use web services such as WCS and WFS as data sources; they access them by an application, usually a desktop GIS. The typical access query is to retrieve a vector or raster 2D coverage that will be used in some spatial analysis or image processing. This *modus operandi* is influenced by the traditional cartographic abstractions of maps, i.e. each coverage is processed separately.

This working model breaks down when one wants to get access to a large EO data set. For example, the MODIS vegetation index

archive for Brazil from 2002 to 2014 has 12.000 independent files. Using WCS to retrieve such data set for analysis, one has to retrieve each file, run the desired algorithm and then move to the next file. Obviously, this way of working is not adequate. Researchers need to address the set of data as whole to run algorithms.

To better understand the requirements of big EO data analytics, consider a conceptual view of the problem. Earth observation satellites revisit the same place at regular intervals. Thus, measures can be calibrated so that observations of the same place in different times are comparable. These calibrated observations can be organized in regular intervals, so that each measure from a sensor is mapped into a three dimensional multivariate array in space-time (see Figure 1). Let  $S = \{s_1, s_2, \dots, s_n\}$  be a set of remote sensing images which shows the same region at  $n$  consecutive times  $T = \{t_1, t_2, \dots, t_n\}$ . Each location  $[x, y, t]$  of a pixel in an image (latitude, longitude, time) maps to a  $[i, j, k]$  position in a 3D array. Each array position  $[i, j, k]$  will be associated to a set of attributes values  $A = \{a_1, a_2, \dots, a_m\}$  which are the sensor measurements at each location in space-time (see Figure 1). For optical sensors, these observations are proportional to Earth's reflection of the incoming solar radiation at different wavelengths of the electromagnetic spectrum.

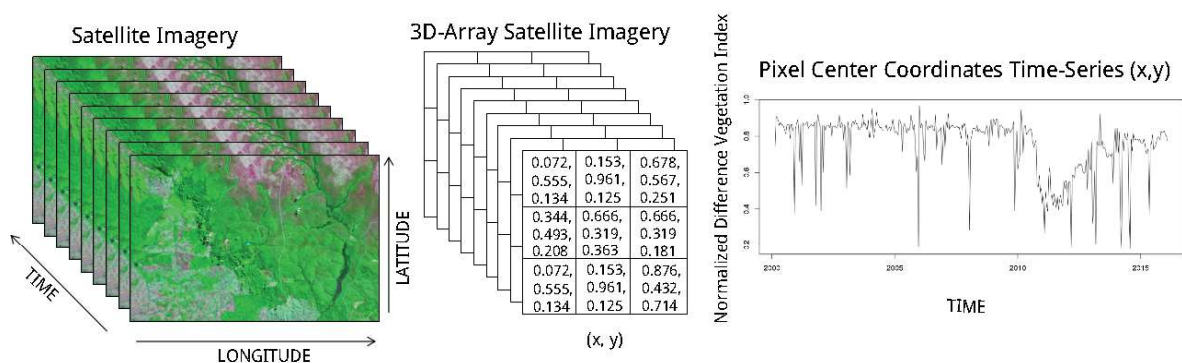


Fig. 1 - A Normalized Difference Vegetation Index (NDVI) time series.

Therefore, a 3D array is a more appropriate conceptual model for big EO data than the 2D map metaphor used in GIS and in most OGC web services.

Using the 3D array metaphor, scientists can approach the classification problem in different ways. They can first classify each

image separately and then compare the resulting classifications in time (the space-first, time-later approach). Alternatively, they can first classify each time series and then join the results in space (the time-first, space-later approach). Combinations of these approaches are also possible. To enable researchers to develop

innovative analytical methods that make good use of big EO data, the system architecture needs to support both approaches. The main question that arises is whether a standard such as WCS supports the 3D array metaphor.

In principle, the concept of WCS could apply to both 2D and 3D arrays. In practice, the current WCS 3D coverage specification is not fully supported by the implementations available that serve only 2D coverages. The OGC WCS can easily handle multivariate coverages, but it is not easy to specify a multivariate, multitemporal coverage in WCS. Furthermore, coverages are still retrieved one by one, thus creating a stack of 2D maps on the client machine. In this way, WCS does not free the user from the burden of dealing with large numbers of individual files. Instead of dealing with a big EO data set as a sequence of maps, as is implicit in WFS and WCS, researchers need new tools. In this perspective, good geospatial web services for big data should be designed to serve the needs of information extraction algorithms. These methods will in general be different from available in a typical GIS.

### 3. WEB TIME SERIES SERVICE

In the previous sections, we argued that the current generation of OGC standards has been designed to match the cartographic metaphors used by today's GIS. We also argued that the 3D array metaphor is better suited for big EO data than the map metaphor. We now consider how to support an important kind of algorithms that extract information from remote sensing time series.

To get a remote sensing time series, one first organizes a large set of EO data as a 3D array. From each pixel location in the array, one can extract a time series of one or more variables for a temporal interval. The benefits of remote sensing time series analysis arise when the temporal resolution of the big data set is sufficient to capture the most important changes. In this case, the temporal autocorrelation of the data can be stronger than the spatial autocorrelation. In other words, given data with adequate repeatability, a pixel will be more related to its temporal neighbors' rather its spatial ones. In this case, *time-first, space-later* methods will give better

results than the *space-first, time-later* approach.

Recent results in the literature show that analysis of satellite image time series enables extracting long-term trends of land change (OLSSON *et al.*, 2005; ADAMI *et al.*, 2012; SAKAMOTO *et al.*, 2005). Such information, which would be harder to obtain by processing 2D, images separately. Algorithms such as TWDTW (MAUS *et al.*, 2016), TIMESTAT (JÖNSSON and EKLUNDH, 2004) and BFAST (VERBESSELT *et al.*, 2010) support these analyses. These algorithms process individual time-series and combine the results for selected periods to generate classified maps.

Motivated by the need to retrieve satellite image time series from large 3D arrays, we have designed and implemented the Web Time Series Service (WTSS). A WTSS server takes as input a 3D array. Each array has a spatial and a temporal dimension and can be multidimensional in terms of its attributes. For example, the dataset showed in Figure 1 represents a time series of the NDVI index extracted from a large 3D MODIS array.

The WTSS service is independent of the actual data architecture used for 3D array store. It can work with solutions such as flat files, MapReduce distributed datasets, array databases or object-relational databases. We have implemented the service using both a set of flat files and the SciDB array database management system with the same external interface. The WTSS interface provides three operations:

1. *list coverages*: this operation allows clients to retrieve the capabilities provided by any server that implements WTSS. Or simply put, it returns a list of coverage names available in a server instance. The server response is a JavaScript Object Notation (JSON) document. The names returned by this operation can be used in subsequent operations (see example in Figure 2).
2. *describe coverage*: this operation returns the metadata for a given coverage identified by its name. It includes its range in the spatial and temporal dimensions. It also receives a JSON document as a response (see example in Figure 3).
3. *time series*: this operation requests the time series of values of a coverage attribute at a given location (see Figure 4).



Fig. 2 – List coverages operation: [http://www.dpi.inpe.br/tws/wtss/list\\_coverages](http://www.dpi.inpe.br/tws/wtss/list_coverages).

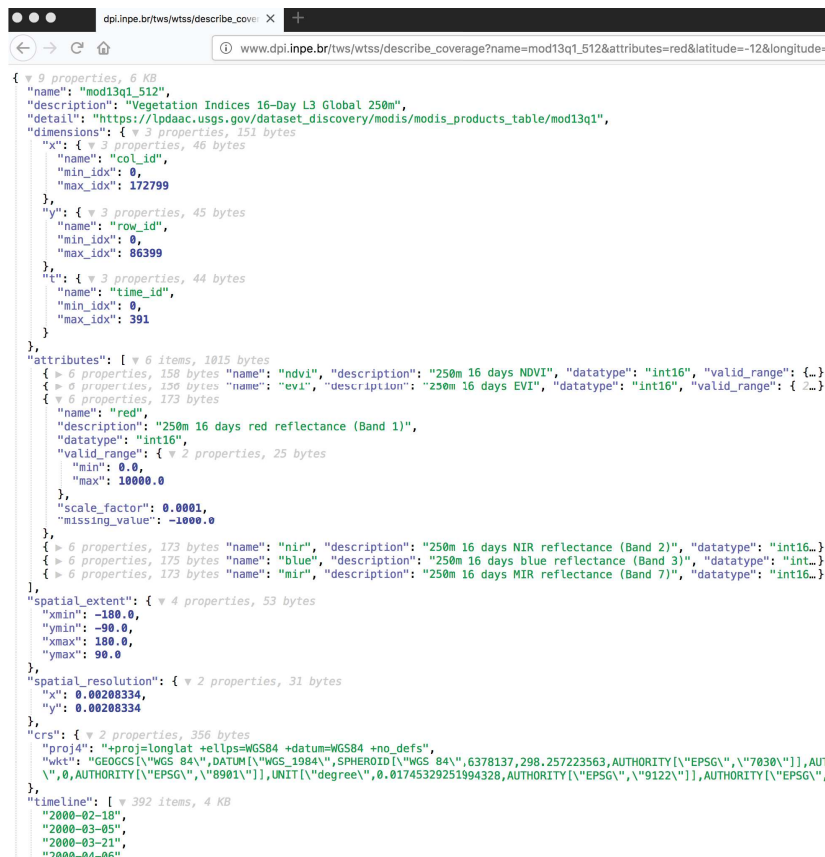


Fig. 3 – Describe coverage operation: [http://www.dpi.inpe.br/tws/wtss/describe\\_coverage?name=mod13q1\\_512](http://www.dpi.inpe.br/tws/wtss/describe_coverage?name=mod13q1_512).

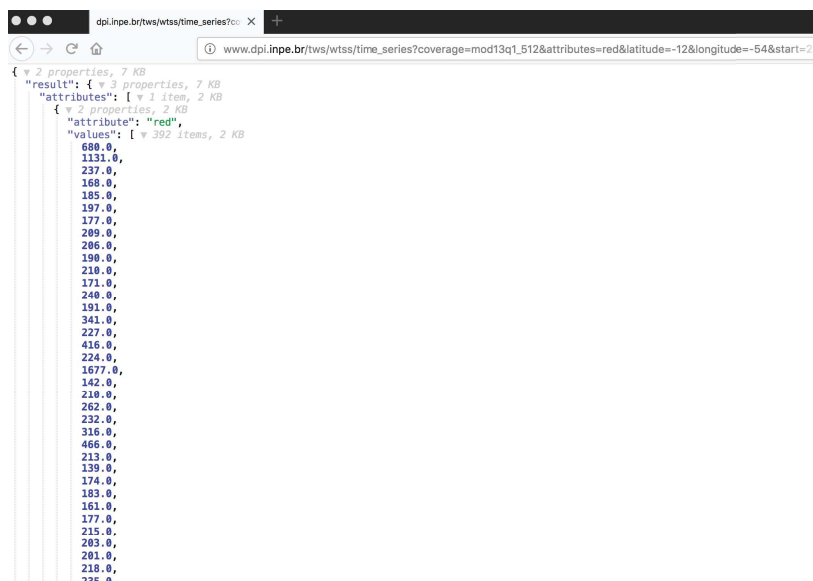


Fig. 4 – Time series operation: [http://www.dpi.inpe.br/tws/wtss/time\\_series?coverage=mod13q1\\_512&attributes=red&latitude=-12&longitude=-54&start=2000-02-18&end=2000-03-21](http://www.dpi.inpe.br/tws/wtss/time_series?coverage=mod13q1_512&attributes=red&latitude=-12&longitude=-54&start=2000-02-18&end=2000-03-21).

WTSS saves time when dealing with huge volumes of data because it closes the gap between big EO data and applications in a flexible and simple API. Syntactically, WTSS is different from OGC standards, since it uses the JSON format instead of XML to deliver complex responses. Writing lightweight web applications for data visualization and retrieval is simpler with JSON. Its more cohesive and short notation helps users of the API to understand how the service works and simplifies decoding by client applications. OGC is considering using JSON based formats, as shown by the draft implementation of the OM-JSON service for Observation and Measurement Data (OGC, 2015a). This shows that OGC recognizes the benefits of the JSON format for lightweight services.

WTSS time series response is also easy to be consumed by statistical computing languages such as R. We have developed an R package that implements the WTSS client to allow researchers to use R methods such as TWDTW (MAUS *et al.*,

2016) and BFAST (VERBESSELT *et al.*, 2010) to analyze large sets of satellite image time series.

#### 4. USING THE WTSS SERVICE

As an example of using WTSS, consider an application that aims at validating thematic maps created from remote sensing imagery. Jensen (2009) points out that there are different types of errors introduced during the mapping process and stress the need for tools to assess the map accuracy, increasing the usefulness and credibility of the data. In a typical web-based validation tool, experts have to analyze different data, such as images with different spatial resolutions, and also the temporal dynamics at the locations represented by the EO time-series values.

Figure 5 shows a web-based validation tool, that includes a graphical display of MODIS/NDVI series. The user interacts with the application by clicking on the map; this will generate a location that will be used in a request to a WTSS server through a JavaScript WTSS client.

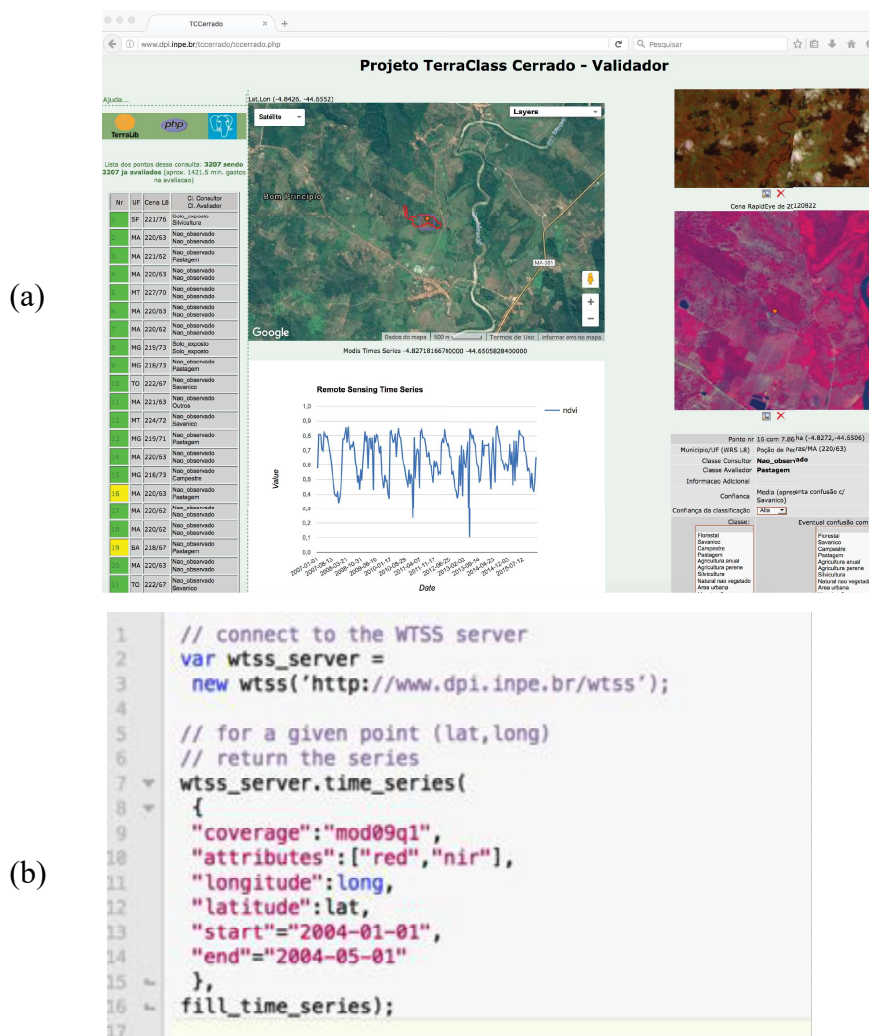


Fig. 5 - The validating tool (a) and the JavaScript client used (b).

Figure 6 shows another web-based application that uses WTSS. In this application, again selecting a location with a click on the map, a user obtains a graphical display of a MODIS/NDVI time series. But the result of the algorithm TWDTW method for land use and land cover mapping (MAUS *et al.*, 2016) using a sequence of multi-band satellite images it also obtained. It

allows scientists to experiment the method in a single location before applying it to a given area. A R implementation of the TWDTW is available at <https://github.com/vwmaus/dtwSat>. This application written in R consumes the MODIS/NDVI time series obtained from a WTSS server, using the WTSS R-client.

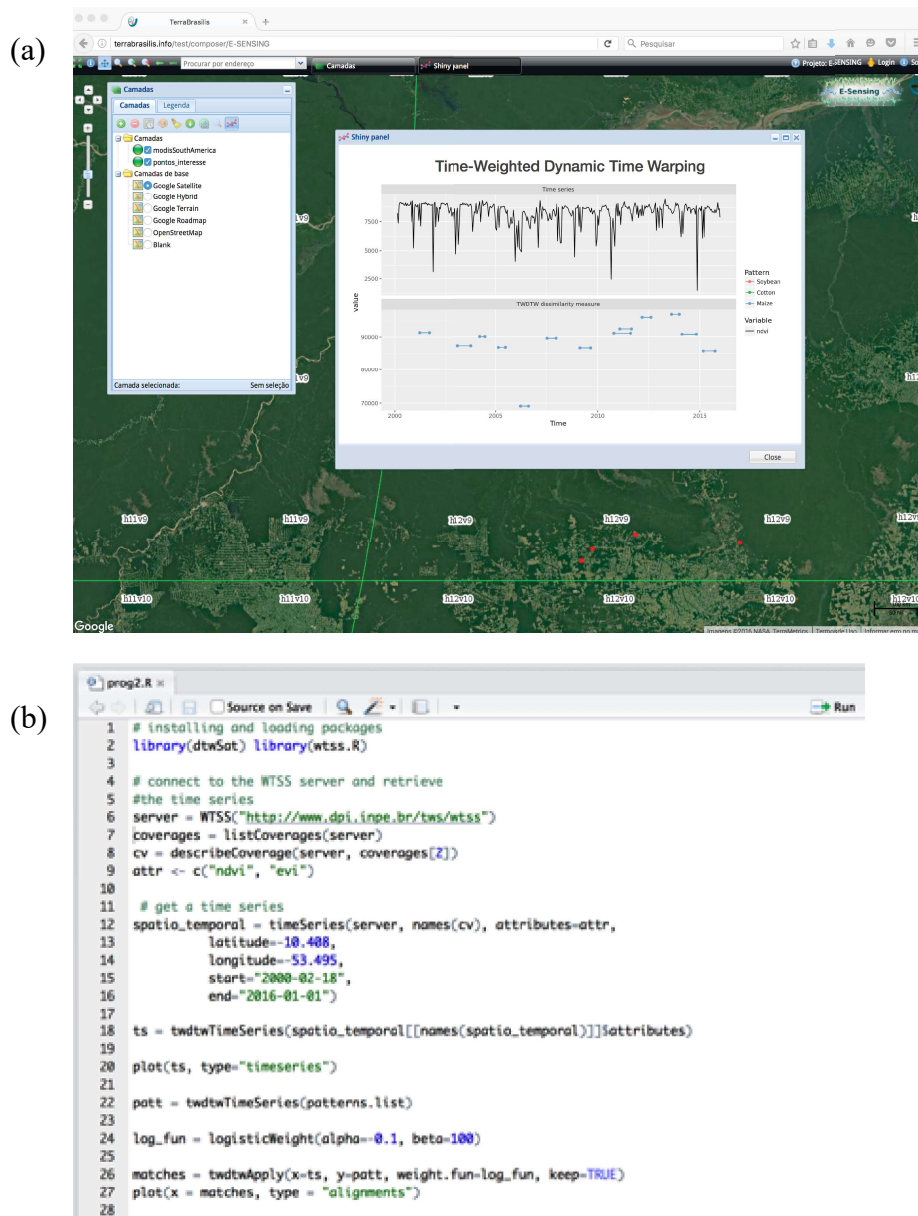


Fig. 6 - A web-based application of the TWDTW algorithm (a) using the WTSS R-client (b).

## 5. Future Directions on Web Services for Big Data

In the previous sections, we have argued that the current design of WCS and WMS limits the use of these standards for dealing with big EO data sets. We have also presented WTSS, an example of a service designed to work with big

data. In this section, we examine some future directions for web services suited for big EO data.

Given the burden of transferring large data sets over the Internet, web services for big data should be concerned with performing server-side processing, rather than supporting client-side retrieval. Instead of downloading large data files,

such web services would enable algorithms to be run on a remote server. This points to an emphasis on web processing services.

There are two OGC web services designed for data processing: the WPS Web Processing Service (OGC, 2015b) and the WCPS Web Coverage Processing Service (BAUMANN, 2010). WPS standardizes how clients can invoke the execution of a process. Thus it focuses on the description of requests and responses to inputs and outputs. It is not concerned on how to express the processing on the server side. Müller et al. (2010) built an architecture using WPS where client applications can move the code to the server in order to perform operations. However, WPS requires the web server to provide the needed operations, which is not currently the case with big EO data. Researchers are still in the stage of experimenting with new methods. Rather than providing a pre-defined set of algorithms, the server-side processing service should be flexible to allow researchers to run their own methods on big data sets.

The WCPS standard proposes a coverage processing language in an attempt to allow clients to express their computations for evaluation by the server. Although endorsed by OGC, this proposal has not been widely adopted. To the best of our knowledge there is only one implementation supporting it as a component of the RasDaMan project (BAUMANN *et al.*, 1998). Furthermore, the WCPS standard is based on a sequence of pixel-by-pixel operations over a set of 2D coverages. The basic request structure of WCPS consists of a loop over a list of coverages, an optional filter predicate, and an expression indicating the desired processing for each coverage (BAUMANN, 2010). This way of working is not flexible enough to include algorithms that work with time-series and for spatio-temporal processing. This is illustrated by the work of Karantzalos *et al.* (2015), where the WCPS service was only used for data retrieval, and the classification algorithm was run in the client machine using open source libraries.

One of the challenges in designing a new language for coverage processing is the diversity of algorithms and applications already existing and the practices of the research community. Researchers are most productive when working on familiar computing environments. Scientists

like to test new ideas on small and well-known data sets. Only after they are satisfied with the experiments, they are willing to work with big data. Therefore, a standard for big Earth observation data analytics should meet important needs of the research community:

1. Analytical scaling: support for the full cycle of research, allowing algorithms developed at the desktop to be run on big databases with minor or no modifications.
2. Software reuse: researchers should be able to easily adapt existing methods for big data, with minimal reworking.
3. Collaborative work: the results should be shareable with the scientific community, and different research teams should be able to build their own infrastructure.

Data scientists are conservative in their choice of tools. They prefer to work on tools with a simple software kernel where they can easily add new packages that encapsulate new analytical methods. A prime example is the **R** suite of statistical tools (R CORE TEAM, 2015). **R** provides a wide variety of statistical and graphical tools, including spatial analysis, time-series analysis, classification, clustering, and data mining for many disciplines (e.g. hydrology, ecology, soil science, agronomy). It is extensible through high quality packages. It provides methods and tools in an open source environment and allows research reproducibility. Using **R** as their primary tool for big data analytics, researchers can thus scale up their methods, reuse previous work, and easily collaborate with their peers. Therefore, we consider that tailor-made, simpler, APIs that support **R** programming can be more effective for processing big EO data than requiring scientists to re-implement their methods on a new coverage processing language.

For future work, we envision a web service for processing big EO data as a simple and standardized interface that can be used with a few commands. It would let users encapsulate their algorithms for server-side processing. Such a service would go beyond what is currently offered by OGC standards such as WPS and WCPS to allow progress on big EO data analytics. Researchers would be able to develop and share new methods, working on a familiar **R** environment. They would be able to test their methods on their desktop before running



experiments on big data sets. Such a service that would allow significant progress on big EO data analytics.

## 6. CONCLUSIONS

This paper addressed the problem of how to design and build technologies that allow the EO community to explore the unprecedented amounts of satellite data available for research and operational use. We investigate if the implicit decisions taken by OGC when designing services such as WMS, WCS and WFS allow them to be used for big EO data. We also consider whether new kinds of web services are required to handle big EO data efficiently.

We conclude that the current OGC standards, and their implementations, can not be considered to be the most appropriate ones to handle big EO data sets since they are inspired by the traditional cartographic abstractions of maps, where each coverage is processed separately. The most innovative analytical methods that make good use of big EO data also require a conceptual view of big EO data sets as 3D arrays of data, where each array position  $[i, j, k]$  will be associated to a set of attributes values  $A = \{a_1, a_2, \dots, a_m\}$ , which are the sensor measurements at each location in space-time. This conceptual view allows the two approaches for data processing *space-first, time-later* and *time-first, space-later* shown in the paper.

We argue that tailor-made, simpler, APIs can be more effective than generic services such as WMS and WCS for accessing big EO data, specially aimed at data analytics on 3D arrays, where the temporal component is of crucial importance. As an example of such tailor-made service we describe the Web Time Series Service (WTSS). We show how WTSS closes the gap between big EO data and applications consuming time-series of data in a flexible and simple API that uses the JSON format to delivery complex responses.

This is the first step to realize a vision of a web service for processing big EO data as a simple and standardized interface that can be used with a few commands and let users encapsulate their algorithms for server-side processing.

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