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e-Sensing:
Big Earth observation data analytics
for land use and land cover change information

Final Report: 01 January 2015 – 31 December 2018

Host institution: INPE – Instituto Nacional de Pesquisas Espaciais

Principal investigator: Gilberto Câmara (INPE)

Research team: Ieda Sanches, Karine Ferreira, Leila Fonseca, Lubia Vinhas, Isabel Escada, Gilberto Queiroz, Luiz Maurano, João Vianei Soares, Julio d'Alge, Pedro Andrade, Ricardo Cartaxo, Thales Körting.

Additional investigators: Eduardo Llapa (INPE)

Project website: http://www.esensing.org

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1 Overview of the project objectives

This document provides the final report of the "e-sensing" FAPESP project (grant 2014/08398-6), and describes the activities carried out during the period 01.01.2015 to 31.12.2018. We will use numbers (such as [10]) to refer to the list of papers published, available in the References section.

Currently, scientists ignore the time reference inherent to Earth observation data, producing land cover maps taking either a single or at most two time references. As a result, only a small part of the big data sets produced by remote sensing satellite are ever used. This leads to an important research question: *How can we use e-science methods and techniques to substantially improve the extraction of land use and land cover change information from big Earth Observation data sets in an open and reproducible way?*.

In response to this challenge, *our project will conceive, build and deploy a new type of knowledge platform for organization, access, processing and analysis of big Earth observation data*. The key elements of this knowledge platform are:

1. A scientific database based on the innovative big data management system, capable of managing large remote sensing data sets.
2. An innovative set of spatiotemporal image analysis methods, mostly based in analysis of satellite image time series. These methods are all developed as open source software to promote reproducibility.

The innovative infrastructure developed in the project will be used for new types of information extraction from Earth observation data, focused on land cover and land use change of large data sets. Our knowledge platform will allow scientists to perform data analysis directly on big data servers. Scientists will be then able to develop completely new algorithms that can seamlessly span partitions in space, time, and spectral dimensions.

We aim to make two important contributions:

1. New database methods and techniques that use array databases to build a geographical information system that handles big spatial data.
2. New data analysis, data mining, and image processing methods to extract land change information from large Earth observation data sets.

2 Main results of the project

Our most relevant results are divided in two groups: those related to advances in big Earth observation data analysis software, and new application results based on new data analysis techniques.

In the area of data analysis software, the main results were:

1. New time series analysis, machine learning and deep learning methods that allow high accuracy in land use and land cover classification using satellite image time series [1] [3] [8] [14] [15].
2. Implementation of SITS, an R package for working with satellite image time series. It includes data retrieval, clustering, and provides machine learning methods for time series classification, including SVM, LDA, QDA, GLM, Lasso, Random Forests and Deep Learning [36].
3. Proposal, development and validation of a spatiotemporal calculus for reasoning about land use change dynamics [2].
4. New methods for space-time segmentation of satellite images [9] [19] [23] [30].
5. New methods for clustering of satellite image time series data using SOM (self-organizing maps) [39].

In the applications area, the main results were:

6. Development of a new land use and land cover map for the state of Mato Grosso, from 2000 to 2016, in cooperation with EMBRAPA [3].
7. Advances in the understanding and modelling of tropical forest ecology and degradation [12][16][17][18] [28] [29].
8. Production of data sets and ground studies which are useful for validating multi-temporal land use classification methods [4] [5] [6] [13].
9. Evaluation of existing land cover classifications to serve as baseline for the results of the e-sensing project [10][11][26].

Overall, the project has achieved its main goals. We were able to develop new methods for big Earth observation data analysis and provide support for innovative applications that use e-science methods. These methods have been validated in large scale experiments that use big data.

3 Detailed description of the results

This section describes the results of the project. In the presentation, we follow the project organization in three work packages (WP), and associated milestones, as laid out in the proposal:

1. *WP 1 – Databases*: research and development associated with using array databases to store large Earth observation data sets and developing workflows and methods for efficient storage, access and processing of large data, reproducibly.
2. *WP 2 – Data analysis*: R&D on spatiotemporal techniques for extracting change information on large Earth observation data sets, relevant for forestry applications; include novel time series applications for remote sensing data, and combined time series and multi-temporal image processing.
3. *WP 3 – Use case development*: case studies of forestry and agriculture applications that use large Earth observation data sets. These use cases will validate the methods and data developed by the other work packages.

For each work package, we preview the result more directly associated with it. The rest of the results of the project can be found in the References section. All of the papers published by members of the research teams that are associated to the project are available at the project's website: http://www.esensing.org.

3.1 Results on Big Earth observation databases

This task builds databases to be used by the project. In our original proposal, we had envisaged to use the array database SciDB for Earth observation applications. However, as the project developed, we found that the use of cloud computing to be a more cost-effective way of working with big Earth observation data.

In the first and second year of the project, we worked with the array database SciDB to perform analysis of big Earth observation data. We found out that setting up a computing environment for big data requires a substantial investment in computing infrastructure and data management. In the third and fourth year, we decided to evaluate the alternative of using cloud services such as the Amazon Web Services (AWS) and Google Earth Engine. When the project was proposed in mid-2014, it was felt that these systems were not mature enough for consideration. However, these services have evolved enormously in the last five years and the cloud computing model is becoming the prevailing mode of work for most medium and large-scale EO applications.

Cloud solutions archive large satellite-generated datasets and provide computing facilities to process them. By using cloud technologies, users can share big EO databases and minimize the time to data utilization. This choice leads to optimized infrastructure investment and increases data and software sharing and reuse. Both

Google and Amazon are now providing access to terabytes of free Earth observation data, with their platforms Google Earth Engine (https://earthengine.google.com/) and „Earth on AWS" (https://aws.amazon.com/earth/).

However, the cloud computing model also brings governance and institutional challenges. For institutions such as INPE, which have a mission of long-term storage, management and distribution of satellite data produced by the Brazilian space program. For this reason, it is important that INPE considers that it is important to avoid the *vendor lock-in effect*, when users become dependent on a vendor for products and services, unable to use another vendor without substantial switching costs. Therefore, we compared Google Earth Engine with Earth on AWS to understand the impacts of such choices on the long-term policies that result from INPE's mission.

As defined by Google, Earth Engine is "*a platform for scientific analysis and visualization of geospatial datasets, for academic, non-profit, business and government users*". It is free for research users, and available for commercial services under terms that are not public. It hosts a public data archive of open access imagery and provides a proprietary API and a scripting language for data analysis. The algorithms provided in its API are proprietary and have been developed to work efficiently in big data sets, and include machine learning methods. Users can load their own data, retaining their IP rights and develop algorithms using the GEE API, to which their also retain the IP rights. However, Google promotes its use as a research platform, rather than an operational service. Furthermore, the technologies deployed are proprietary and have the potential for a substantial vendor lock-in effect.

Earth on AWS is a *platform* rather than a *service*. Amazon provides an efficient cloud computing environment, with a clear separation between computing and storage servers. The platform hosts a large collection of public Earth observation data from LANDSAT, SENTINEL, CBERS, MODIS and other space-borne systems. All data on this collection can be assessed using the GDAL public API. Since it is not a service, all users have to develop their processing environment and deploy it using virtual machines. A typical AWS user processes data on a virtual machine with an open source data analysis suite such as those provided by **R** or **Python.** There is no transfer of IP rights to Amazon, and users retain ownership of all of the applications they develop. Using AWS does not directly entail *vendor lock-in*. In principle, any AWS-based application could be redeployed to other cloud platforms. In practice, what will control the switching costs from AWS to other vendors is the *economy of scale* effect. As more data is added to AWS, more users will be compelled to choose it if the usage cost is compatible with other vendors. Competing with AWS requires competitors to match their data, infrastructure and cost, which requires significant up-front investment.

Based on the above analysis, we considered that AWS would be a suitable option for developing the research tools of the project, provided that we would base all our work on open source tools that could be used in other cloud platforms. We thus obtained a grant from Amazon Web Services (AWS) under their "Cloud Credits for

Research" program. Using this grant, we have loaded in the AWS cloud servers the following data sets, which are available openly without restrictions:

1. MODIS MOD09Q1 images at 250-meter resolution from 2000 to 2017 for the whole of the Cerrado biome, with about 6,500 images associated to 150 billion different satellite image time series. This data set is freely available using the URL https://s3-sa-east-1.amazonaws.com/mod13q1-bricks.
2. Selected LANDSAT images at 30-meter resolution from 2013 to 2015 for the Cerrado biome, with 6,300 images for 15 scenes, producing about 300 billion different satellite image time series. These images are available using the following URLs:
   https://s3-sa-east-1.amazonaws.com/ landsat-wrs-219-075
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-221-065
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-221-068
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-221-069
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-221-070
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-221-086
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-224-062
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-224-063
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-224-073
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-225-063
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-226-064
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-230-065
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-232-066
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-232-067
   https://s3-sa-east-1.awazonaws.com/landsat-wrs-233-067

Our strategy for developing new methods for big Earth observation data analysis using AWS has the following aims:

1. *Analytical scaling:* provide support for the full cycle of research, allowing algorithms developed at the desktop to run on big databases with minor changes.
2. *Software reuse*: allow researchers to adapt existing methods for big data with minimal reworking.
3. *Collaborative work*: enable results to be shared with the scientific community.
4. *Replication*: encourage research teams to build their own infrastructure.

For this reason, in the project our new software uses the R suite of statistical tools as the environment to develop our analytical methods. R is the *lingua franca* of data analytics. Using R, researchers can scale up their methods, reuse previous work, and collaborate with their peers. Our aim is to be able to execute the same script in both client and server side.

3.2 Results on data analysis for big Earth observation data

3.2.1 Web time series services and web-based exploratory big data analysis

The Web time series service (WTSS) is an important result of the project [37][98]. WTSS is a lightweight web service. The client allows Earth observation users to obtain time series from data sets available in a Web Time Series Server. The functions include: (a) listing the data sets available in the server; (b) describing the contents of a data set; (c) retrieving a time series based on spatial location and temporal filters. WTSS saves time when dealing with huge volumes of data because it has a flexible and simple API. It uses the JSON format instead of XML to deliver complex responses, which are then easily consumed by R [98]. The WTSS is fully operational. To visualize data from a WTSS server, we developed a web-based interface exploratory big data analysis, shown in Figure 2. The interfaces use WTSS to obtain time series data. The user can then analyse the data using the methods available in the **sits** R package, developed by the project team (see description below).

Figure 1 – Web-based exploratory big EO data analysis interface. (source: e-sensing team).

3.2.2 The Time-weighted Dynamic Time Warping method

One of the relevant new results of the project is the Time-weighted Dynamic Time Warping method (TWDTW) for analyzing satellite image time series. This research has been published in leading journals [1][15], and has already been cited more than 50 times, according to Google Scholar. This result is associated to a PhD dissertation [122].

This new algorithm is based on the dynamic time warping (DTW) method used in time series data mining. DTW works by comparing a temporal signature of a known event (e.g. *a* person's speech) to an unknown time series (e.g. a speech record of unknown origin). The algorithm finds the optimal alignment between two series and provides a robust dissimilarity measure as a result. The original DTW algorithm works well for shape matching, but is not suited *per se* for satellite image time series classification. It disregards the temporal range when finding the best alignment between two series. Since each land cover class has a distinct phenological cycle that is relevant for space-time classification, a good time-series classifier for remote sensing data needs to balance between shape matching and temporal alignment. For example, the soybean cycle ranges from 90 to 120 days. A time series with similar shape but with much larger cycle is unlikely to come from a soybean crop.

To improve the standard DTW, we introduce in [15] a time constraint that helps to distinguish between different types of land use and land cover classes. The resulting algorithm is called *time-weighted dynamic time warping* (TWDTW). It is a significant improvement on standard DTW for land use and land cover classification of satellite image time series, since it allows users to introduce time constraints associated to the agricultural calendar. In the Brazilian Cerrado, for example, farmers plant soybeans in end of the year (October to December) and harvest in February. Corn or cotton are planted in March and harvested in July. These time constraints are necessary for good classification of satellite image time series (see Figure below).

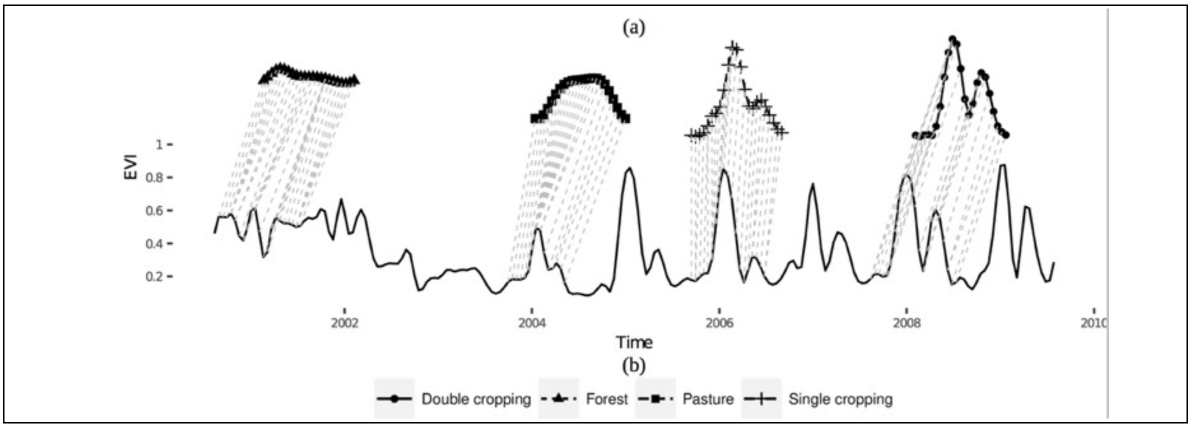

Figure 2 – TWDTW matching between known samples and a satellite image time series (source:[15])

We ran a case study in an area in the Porto dos Gaúchos municipality, that covers 7,000 km^2 in the state of Mato Grosso, Brazil. In 2013 its deforested area was 3023 km^2, that is 43% of the original forest. The cropland area grew from 60 km^2 in 2000 to 581 km^2 in 2013. We classified matches in the time series as either *forest, secondary vegetation, pasture, single cropping, or double cropping*. These classes are the most relevant ones for our study on trajectories of change in Amazonia. Our proposed logistic time-weighted version achieved an overall accuracy of 87%. We also compared our classification with the MODIS land cover product, currently the only global land cover product available yearly (Table 1). Results show a better performance of TWDTW. We thus consider that TWDTW is an innovative and promising approach, that needs to be further investigated in larger areas.

TABLE 1

Assessment of MODIS Land Cover and TWDTW for Porto dos Gaúchos (source:[15])

	Reliability		Accuracy	
Class	MODIS	TWDTW	MODIS	TWDTW
Forest	87%	94%	77%	88%
Pastureland	67%	88%	85%	85%
Cropland	89%	92%	75%	96%

3.2.3 The SITS package for satellite image time series data analysis

The **sits** package ("Satellite Image Time Series") includes data retrieval from a WTSS (web time series service), different visualization methods for image time series, smoothing methods for noisy time series, and different clustering methods including dendrograms and SOM [36]. It matches noiseless patterns with noisy time series using the TWDTW method for shape recognition and provides machine learning methods for time series classification. To our knowledge, **sits** is the first R package that provides a unified support for machine learning methods for satellite image time series. The package includes an advanced method for data clustering based on self-organized maps (SOM), and also links to a recent advances on spatiotemporal interval logic, both described in the next section.

The methods available for machine learning in sits include:

- *Support vector machine* (**svm**): a classifier that uses linear and non-linear mapping of the input vectors into high-dimensional spaces, building hyperplanes that allow distinguishing between the data classes.
- *Random Forest (***rfor***):* ensemble learning method for classification, that works by building a multitude of decision trees at training time.
- *Linear Discriminant Analysis (***lda***)*: a method that finds a linear combination of features that characterizes or separates the desired classes.
- *Quadratic Discriminant Analysis* (**qda**): A methods that separate measurements of two or more classes of objects by a quadric surface.
- *Multinomial logistic regression* (**mlr**): method that generalizes logistic regression to multiclass problems. It does not assume statistical independence of the input random variables.
- *Deep learning* using *multilayer perceptrons (***dl-mlp***)*: A method that uses a cascade of multiple layers of neural networks with nonlinear processing units.

To compare the performance of these methods, we used a data set with 11.743 samples of 11 classes for the Brazilian Cerrado biome. The fact that different classifiers (*svm, random forest, deep learning*) are able to obtain high accuracy with the same data set shows that the quality and quantity of the sample sizes are the controlling factors in the classification performance.

TABLE 2

Discriminative Power of Machine Learning Classifiers for the Cerrado Data Set

	Reliability			Accuracy		
Class	svm	rfor	dl-mlp	svm	rfor	dl-mlp
Forest	96%	98%	93%	99%	99%	99%
Cerrado strictu sensu	89%	94%	81%	77%	62%	63%
Cerrado campo	92%	85%	89%	97%	98%	94%
Cerrado rupestre	98%	95%	93%	97%	95%	97%
Fallow-Cotton	95%	94%	91%	99%	94%	93%
Millet-Cotton	99%	99%	91%	98%	90%	88%
Pasture	95%	94%	93%	95%	86%	94%
Soy-Corn	97%	94%	96%	97%	97%	95%
Soy-Cotton	97%	96%	94%	97%	95%	96%
Soy-Fallow	99%	92%	97%	99%	93%	99%
Soy-Millet	77%	45%	69%	82%	85%	57%

In the above table, the column *reliability* ("user's accuracy") shows the probability that a pixel labeled as a certain land-cover class in the map is really this class. The figures in column *accuracy* (also known as "producer's accuracy") refer to the probability that a certain land-cover of an area on the ground is classified as such. Thus, we can state a rule-of-thumb for good satellite image time series classification is simple: *first, obtain a large sample size of very good quality; then, use all the data available. If possible, compare the performance of the advanced classifiers (svm, rfor, deep learning) and choose the one that best discriminates your data. If pressed by time or resources, use a support vector machine.*

The **sits** package is available as free and open source software in the project's **github** page: https://github.com/e-sensing.

3.2.4 Spatiotemporal calculus for reasoning about land use change dynamics

Another relevant published research result published in the project is the proposal and development of a spatiotemporal calculus for reasoning about land change dynamics [2][38], associated to a PhD dissertation [119]. When analyzing Earth observation data, scientists are particularly interested in *land use trajectories*, which are paths from one land use into another. Typical questions researchers would like to ask are: *Which forest areas were degraded from 2000 to 2017? When did new agricultural systems such as double-cropping were introduced in the regions? Which area changed for pasture to croplands in the past decade?* To allow researchers to reason about these and similar change, we propose a land use change calculus (LUC Calculus), composed of the following primitives:

1. The interval temporal predicates proposed by Allen[1].
2. The additional predicates FOLLOWS and PRECEDES for comparing time intervals.
3. The new set of predicates RECUR, CONVERT and EVOLVE for reasoning on composition of land use transitions.

Using these predicates, we can express complex queries about land use change trajectories. One example is distinguishing secondary vegetation from mature forest. Mature forests have high biomass and biodiversity, and have not been affected by recent human actions. Secondary vegetation areas are places where the original forest was cut and the area was later abandoned. After a few years, these areas will appear in remote sensing images as forests. However, their biodiversity and biomass is much smaller than that of a mature forest. Thus, it is important to identify areas of secondary vegetation, even though they appear to be mature forest.

As an example, we classified the different types of land use in the municipality of Itanhangá (MT), from 2001 to 2016 (see figure 3). We use the full history of the area considered as a set of land use change trajectories. For an area to be singled out as secondary vegetation, its initial state is classified as “Forest”. Then the area is converted to pasture or cropland, and later abandoned so that the forest regrows. Table 4 shows the logical expression used to uncover areas of secondary vegetation, and Figure 5 presents the total area of secondary vegetation since 2002. Results show that a significant portion of the deforested area was abandoned and has regrown as a forest. This result points out to the predatory nature of deforestation in Amazon. Farmers sometimes cut mature forest and cannot sustain a profitable economic activity in these areas. Using the expressive power of the LUC Calculus, these transitions can be highlighted and better understood.

Table 3

LUC Calculus expression to find areas of secondary vegetation

Searching for all forest areas that have been replaced by pasture, *cerrado*, single cropping or double cropping and turned into forest areas again.

$$\forall\ l \in L, t_1 = [2001, 2002], \forall\ t_i \in T, t_i \neq t_1,\ RECUR(l, \text{“}Forest\text{”}, t_1, t_i)\ \wedge$$
$$(\ EVOLVE(l, \text{“}Pasture\text{”}, t_1, \text{“}Forest\text{”}, t_i) \vee EVOLVE(l, \text{“}Cerrado\text{”}, t_1, \text{“}Forest\text{”}, t_i) \vee$$
$$EVOLVE(l, \text{“}Single\_cropping\text{”}, t_1, \text{“}Forest\text{”}, t_i) \vee$$
$$EVOLVE(l, \text{“}Double\_cropping\text{”}, t_1, \text{“}Forest\text{”}, t_i)\ )$$

[1] J. F. Allen. Maintaining knowledge about temporal intervals. *COMMUNICATIONS OF THE ACM*, 269110:832–843, 1983

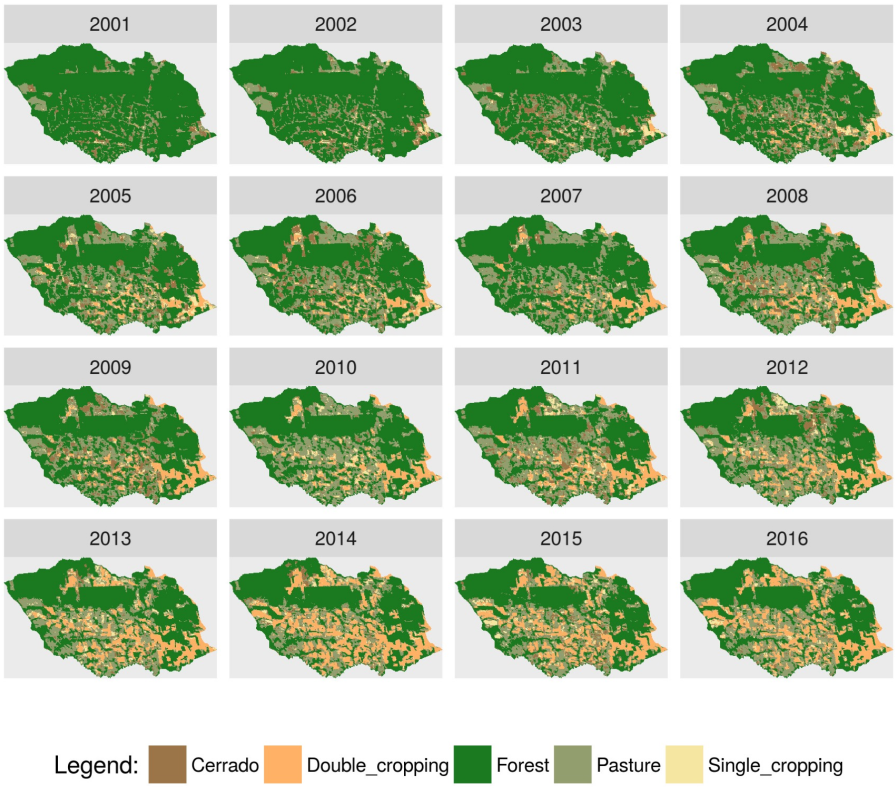

Figure 3 - Land use in Itanhangá, MT, Brazil, from 2001 to 2016

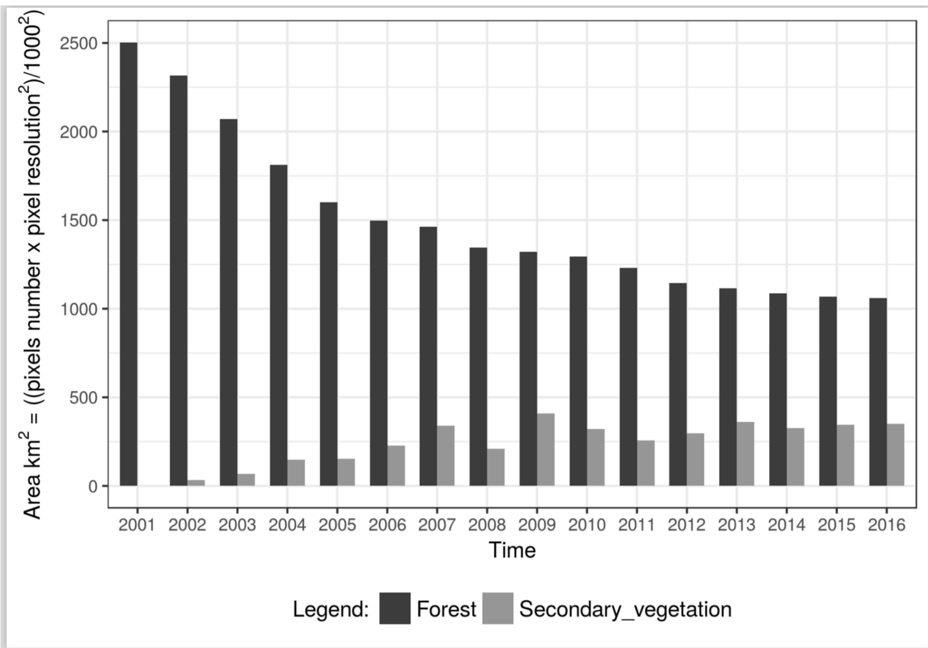

Figure 4 – Total area of forest and secondary vegetation in Itanhangá: 2001 to 2016.

3.2.5 Self-Organizing Maps in Earth Observation Data Analysis

A recent research result by the project is the development of methods for clustering satellite image time series using self-organizing maps (SOM) [39,40]. The objective of the SOM methods is to support the creation of land use and land cover maps from satellite image time series. Such methods (including those discussed in the previous sections of this report) require a training phase using land use and cover samples labeled *a priori*. These training samples must properly represent the land use and cover classes to be identified by the classifier. The quality of these samples is crucial in the classification process. Representative samples lead to good LUCC maps.

We use SOM is a clustering method suitable for time series data sets. Using SOM in the training phase, we can produce metrics that indicate the quality of the training samples and we can also evaluate which spectral bands and vegetation indexes are best suitable for the separability of land use and cover classes. The Figure below shows how the SOM method fits in the overall classification process of satellite image time series. Our approach explores two main features of SOM: (1) the topological preservation of neighborhood, which generates spatial clusters of similar patterns in the output space; and (2) the property of adaptation, where the winner neuron and its neighbors are updated to make the weight vectors more similar to the input.

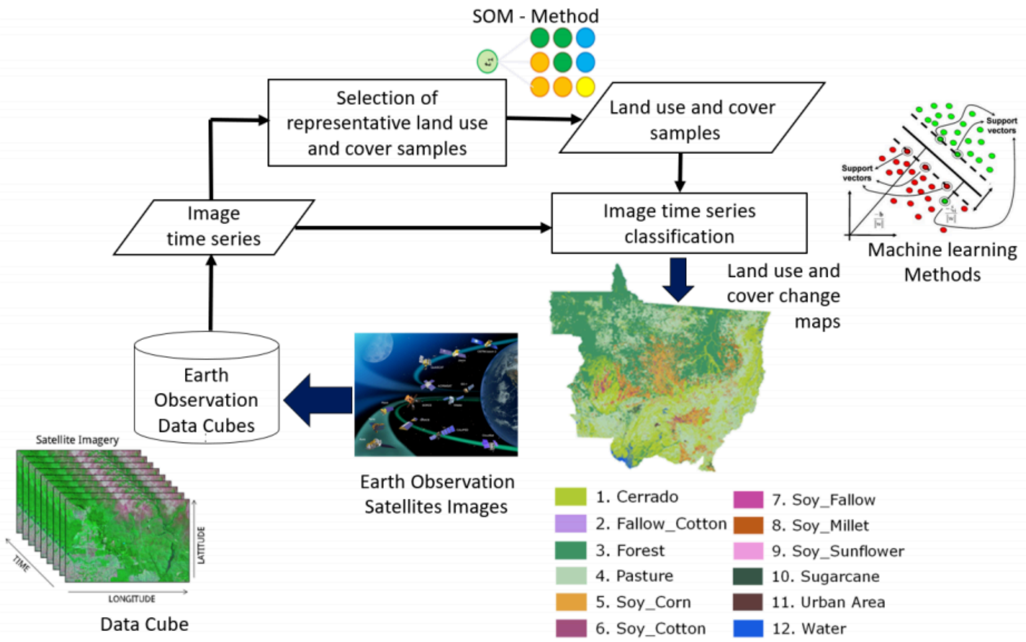

Figure 5 – Using SOM to improve the training samples used for land use classification of satellite images.

To assess the potential of SOM method in the selection of good quality land use and cover samples from satellite image time series, we ran a case study using satellite image time series form the MODIS sensor from 2001 to 2016 in a study area in the Mato Grosso State in Brazil [39]. Each sample has a spatial location (latitude and longitude), start and end date that corresponds to agricultural year (from August to September), the label of the class that corresponds to the sample, and the set of time series with multiple attributes. In this case study, we used the attributes EVI, NDVI, NIR, MIR, BLUE and RED. The ground samples include natural vegetation and agricultural classes for the Mato Grosso state of Brazil. The data set includes 2215 ground samples divided in nine land use and cover classes: (1) Cerrado, (2) Pasture, (3) Forest, (4) Soy-Corn, (5) Soy-Cotton, (6) Soy-Fallow, (7) Soy-Millet, (8) Fallow-Cotton and (9) Soy-Sunflower. Our results [39] show that the SOM pre-processing provides a significant improvement on the classification. Our proposed use of SOM for clustering of satellite image time series has been integrated in the **sits** package described in section 3.2.3.

3.2.6 Space-time segmentation

Another relevant result in the project is the initial development of methods for space-time segmentation of Earth observation data [9][23], which has resulted in papers published in indexed journals. We propose a new segmentation method applied to time series of Earth Observation data. The method integrates regions in order to detect objects that are homogeneous in space and time. This approach aims to overcome the limitations of the snapshot model. Study cases were conducted using time series of MODIS and Landsat-8 OLI scenes by applying spatio-temporal segmentation using the Dynamic Time Warping (DTW) measure as the homogeneity criterion.

The algorithm can be expressed by the following steps:

1. Select a sequence of images as input data.
2. Determine similarity threshold.
3. Determine the number and location of the seeds in the image.
4. Compute DTW distance between the time series of the seeds and their neighbors. If they are similar, they are added to the region.
5. Continue examining all the neighbors until no similar neighbor is found. Label the obtained segmented as a complete region.
6. Observe the next unlabelled seed and repeat the process until all the seeds or pixels are labelled in a region.

We tested the algorithm in an overlapping area of two Landsat-8 Operational Land Imager scenes (path/row 219/75 and 220/75), providing a temporal resolution of 8 days. We used 46 enhanced vegetation index (EVI) scenes between July 2014 [Day of Year (DOY) 206] and July 2015 (DOY 209), with a spatial resolution of 30 m. The study area is located in a center-eastern region of the state of São Paulo, Brazil (see Fig. 6). In this test, we used 15 reference polygons based on the static targets observed during the year of image collection. The polygons represent areas of the center-pivot irrigated areas, a eucalyptus, and a lagoon. Seeds have been set in the center of those polygons. The similarity threshold was chosen so that the agricultural, commercial forestry, and water bodies areas could be separated from the other neighboring targets.

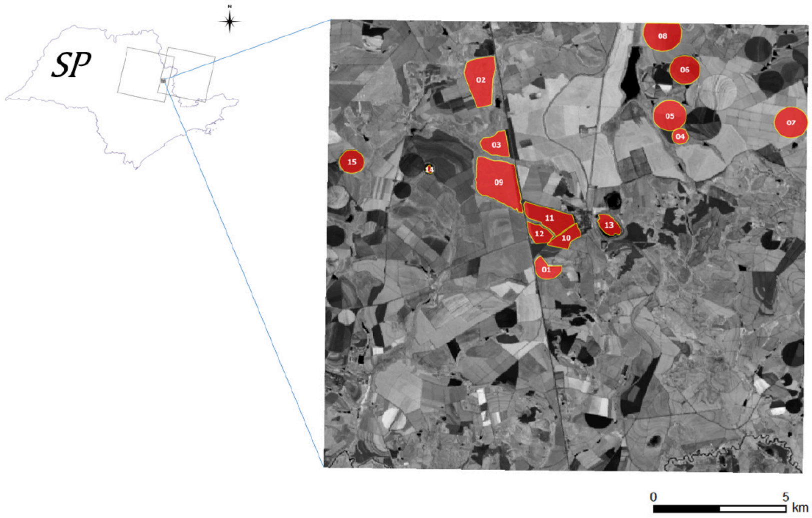

Figure 6 - Ground truth polygons for the test case of space-time segmentation.

Our results show that, using of the DTW similarity method for comparing time series, we could detect most of the ground truth polygons that we used for our test case. The DTW similarity method performs better than other similarity metrics, such as Euclidean distance and Manhattan distance. However, we also found that the use of the temporal dimension increases the complexity of processing compared with the segmentation of satellite images that considers only a single date. Further analysis are needed to apply this approach in regions with higher spatial and temporal resolutions and to test different vegetation indices and other types of satellite image. For more details, please refer to the papers [9] and [23].

3.3 Results on use case development

3.3.1 Detection of forest degradation

In the project, we have developed methods for detecting forest degradation with three papers published in journals [17][28][29]. Forest degradation is defined as defined as *the long-term and gradual reduction of canopy cover due to forest fire and unsustainable logging.* Typically, a mature forest is degraded when part of its tree cover is removed. In the Brazilian Amazonia, degradation is caused by either unsustainable logging practices or by forest fires (intentional or uncontrolled). Understanding and identifying forest degradation is important, because it causes carbon emissions that have to be accounted for and leads to a loss of biodiversity caused by removal of important species. Also, degradation often (but not always) is associated to later actions that cause the full removal of forest cover (deforestation).

In the project, we first carried out a study on the dynamics of forest degradation. The work was published in an indexed journal [17] and is associated to a PhD thesis by Taíse Pinheiro [123]. We performed a detailed analysis of two Amazon frontiers of the 1970s and 1990s using 28 years (1984–2011) of Landsat images. She selected two case studies in two distinct municipalities: (a) Novo Progresso, Southwestern Pará, where logging expansion started in the early 2000; and (b) Sinop, Northern Mato Grosso, Brazil, currently a consolidated frontier. The work uses data mining techniques to build trajectories of forest degradation and to find the relationship between deforestation and degradation.

In Novo Progresso, results show that degradation is more associated to selective logging than to forest fires. Half of the logged forests are not immediately deforested but rather abandoned and subsequently cleared in 3 years. The results showed no regime of recurrent forest fires, nor were forests revisited by loggers in Novo Progresso. Forest degradation is mostly associated to a single logging event. Results also show a change in behaviour of the loggers. In the period 1984–1997, 90% of degraded areas were completely deforested in one year's time. From 2004 onwards, due to increased command and control measures, less degraded areas were completely cut. About 40% of the degraded areas were not completely cleared (Figure 7), leading to large areas of persistent degradation.

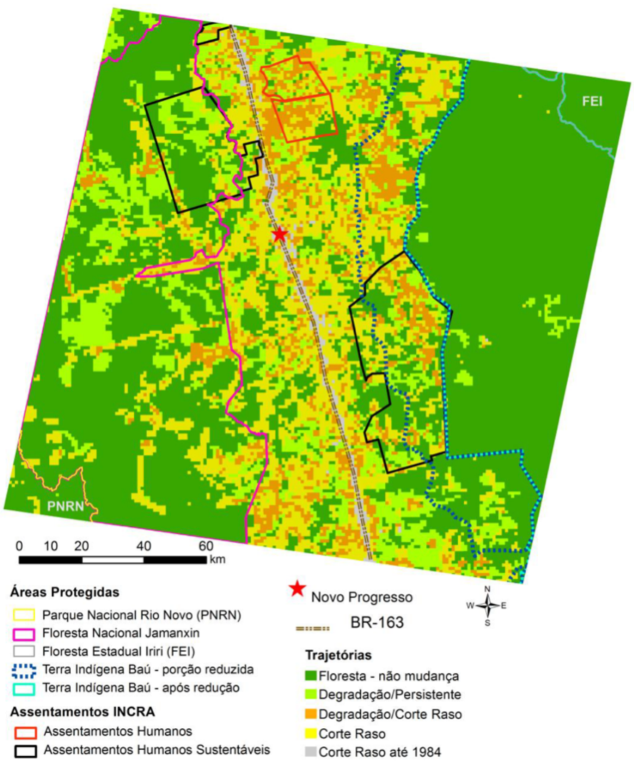

Figure 7 – Forest change trajectories in Novo Progresso (PA) from 1984 to 2011 (source: [122]).

In Sinop, the transition from degradation to deforestation lasts longer, with a typical period of 7 years (50%). There, forests are typically revisited by loggers before forest conversion into clear-cut. In both frontiers, forest degradation was typically characterized by low to moderate intensity forest damage. Although a large proportion of logged forest was deforested, 40% of the degraded forest areas were not completely deforested. Thus, both in Sinop and in Novo Progresso, there are substantial degraded areas whose emissions have not been properly accounted for by the current INPE Amazonia monitoring system.

Based on these results, we carried out a detailed study on how to perform semi-automatic classification of forest degradation using LANDSAT-8 images[28][84][85], associated to a MSc thesis [132]. The method has the following steps:

a) Classify each image using a spectral mixture model, producing an index image that combines the soil and vegetation fractions.
b) Identify and map on the resulting image features associated to forest degradation. These features include the presence of areas for wood storage, corridors for transportation, and fire scars.
c) Perform a structural classification of degradation patterns using the GeoDMA[2] with 1 Km^2 cells. The structural classifier uses landscape metrics and decision trees.

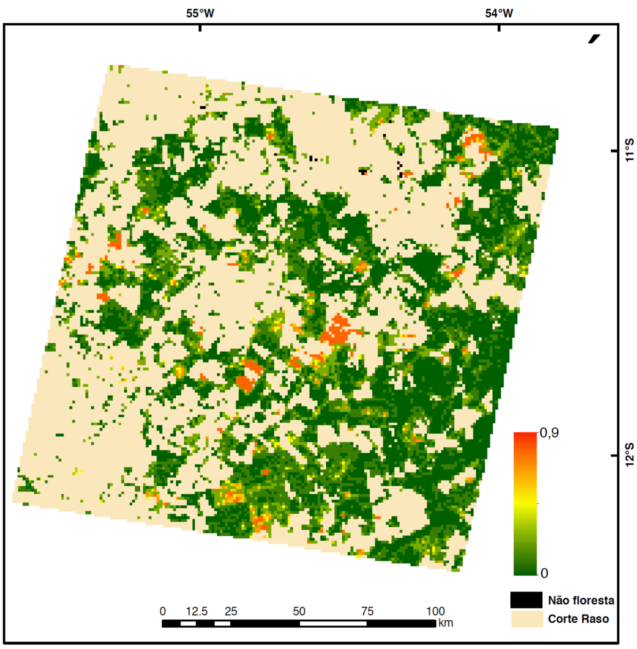

Figure 8 – Gradients of forest degradation intensity for year 2014 for Sinop, MT. The higher the index, the stronger the degradation. Source: [17].

[2] TS Körting, LMG Fonseca, G Câmara, GeoDMA—Geographic data mining analyst. Computers & Geosciences, 2013. This algorithm was developed by the project team on a previous FAPESP thematic project.

The classification accuracy was 96%, measured by comparing with ground samples. The method enabled the production of spatial gradients of forest degradation (see Figure 4). The results show that this approach, considering the intensity of the degradation, can be replicated in temporal studies of analysis of forest landscape conditions. Since each cell is fixed unit in time and space, it is possible to measure the variation of degradation in space and time.

3.3.2 Specification and Validation of Tropical Agriculture Monitoring Methods and Data

The project team developed innovative methods of using satellite image time series to produce land use and land cover classification over large areas in Brazil from 2001 to 2016. The results were published in a peer-reviewed journal [3] and the data has been deposited in an accredited data repository [35]. We used MODIS time series data to classify natural and human-transformed land areas in state of Mato Grosso, Brazil's agricultural frontier. Using the sits R package (see Section 3.2.3 above), we took the full depth of satellite image time series to create large dimensional spaces for statistical classification. Data consists of MODIS MOD13Q1 time series with 23 samples per year per pixel, and 4 bands (NVDI, EVI, NIR and MIR). By taking a series of labelled time series, we fe a support vector machine model with a 92-dimensional attribute space. Using a 5-fold cross validation, we obtained an overall accuracy of 94% for discriminating among 9 land cover classes: *forest, cerrado, pasture, soybean-fallow, fallow-cotton, soybean-cotton, soybean-corn, soybean-millet and soybean-sunflower*. Producer's and user's accuracies of all classes were close to or better than 90%.

The results point out to important trends in agricultural intensification in Mato Grosso. Double cropping systems are now the most common production system in the state, thus increasing the potential for land sparing. Pasture expansion and intensification has been less studied than crop expansion, although it has a stronger impact on deforestation and GHG emissions. Our results show a significant increase in stocking rate in Mato Grosso, and to the possible abandonment of pasture areas opened in the state's frontier. The detailed land cover maps contribute to the assessment of the interplay between production and protection in the Brazilian Amazonian and Cerrado biomes. Two of the resulting classification maps for Mato Grosso (in 2005 and 2016) are shown in Figure 8.

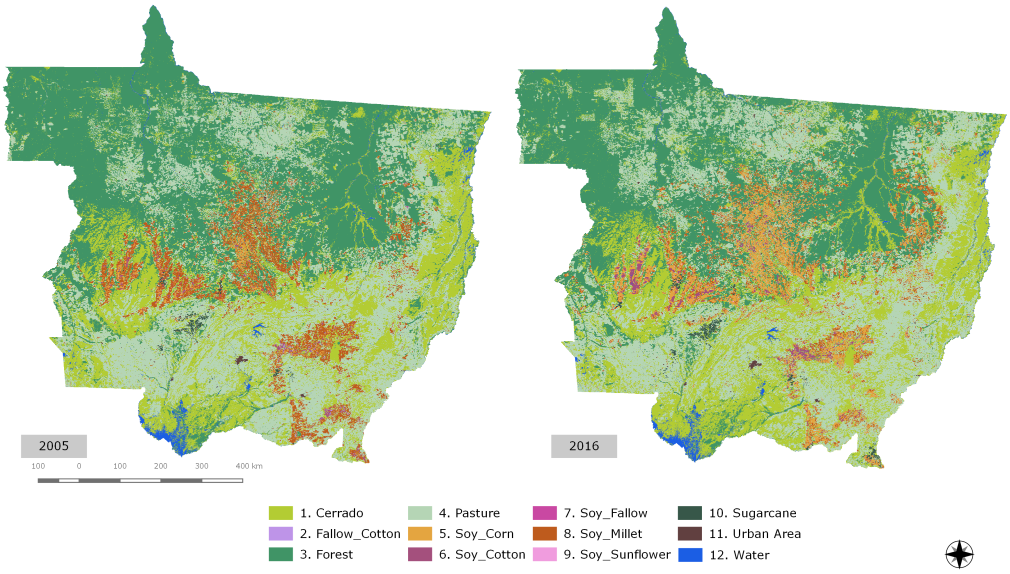

Figure 9 – Land use and land cover classification for Mato Grosso (2005 and 2016).

Among the many significant results we obtained by analyzing the resulting data set, we highlight the change in stocking rate. According to our classification, pasture area in Mato Grosso between 2005 and 2015 declined 4.6 million hectares, from 28.1 to 23.5 million hectares. According to IBGE, the number of cattle heads in the state has increased from 26.7 in 2005 to 29.3 million in 2015, a growth of 10%. In Figure6, we join our results with IBGE data in cattle herds to show that the stocking rate in Mato Grosso has grown steadily. The cattle heads grew by 10%, while pasture decreased by 16% between 2005 and 2015. This is a significant result, because it shows that the relative pressure of cattle raising for increasing deforestation is being reduced. In general, there is a trend towards pasture intensification coupled with abandonment of frontier areas, especially those at the most Northern part of the state.

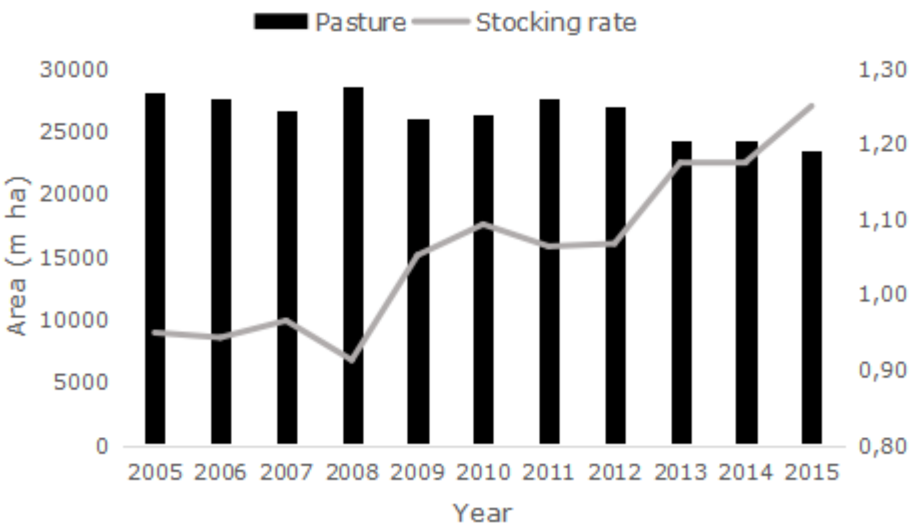

Figure 8 – Change in stocking rate (number of heads of cattle divided by pasture area) from 2005 to 2016 in Mato Grosso.

3.3.3 Collection of field data for supporting classification methods

The project team did extensive fieldwork and collected much ground truth data. These data sets are important to validate our automated methods that work with big EO data. This work has been led by Prof. Dr. Ieda Sanches, who worked on different areas in Brazil to identify their specific characteristics and the define the possible best methods for classification.

Sanches and her associates also worked on a study about the agricultural areas on the state of Rio Grande do Sul. They investigated which of the many possible vegetation indexes extracted from MODIS images produce the best real-time classification. This study was published in *Pesquisa Agropecuária Brasileira,* an ISI-indexed journal [20]. Their conclusion was that the EVI (enhanced vegetation index) enabled the best results. This result is encouraging for the project, since the EVI is one of the indexes used by time series analysis algorithms being developed by the project, as is the case of the TWDTW method described above.

Additionally, Sanches made a field trip in December 2015 to Campo Verde-MT. This a crop-producing area whose products include soybeans (census IBGE 2014: 209,000 ha) and corn as a secondary crop (census IBGE 2014: 95,750 ha). There is a large cotton crop (census IBGE 2014: 69,200 ha). There are single crop areas in more sandy soil and double cropping areas in soils with higher clay content. In the double cropping areas, the second crops include corn, millet, and sorghum. The field work collected more than 1000 ground truth samples, including areas with crops (soybeans, millet, cotton), pasture and forests. This result has been published in an indexed journal [6] and provides good test data for big data analytics. The data is openly available.

A second work by Sanches and co-workers on in suit data production is related to crop production in the Brazilian Cerrado. Her team collected data in Luís Eduardo Magalhães (LEM) municipality, an important Brazilian agricultural area, to create field reference data including information about first and second crop harvests. Moreover, a series of remote sensing images was acquired and pre-processed, from both active and passive orbital sensors (Sentinel-1, Sentinel-2/MSI, Landsat-8/OLI). The results have published in a conference paper [42] and the data is openly available.

Sanches also worked on the issue of Land availability for sugarcane derived jet-biofuels in São Paulo. Since the replacement of fossil fuels by jet-biofuels is one of the main strategies to attain the emission targets, Sanches and co-workers carried out a study was to provide a detailed survey on land availability for sugarcane production in the Brazilian state of São Paulo. Using data from 2013, the results show that more than 3.5 million ha would be potentially available for sugarcane expansion. Almost 80% of the mapped lands have high economic potential once they are located in a distance lower than or equal to 25 km from the processing units. If properly included in the productive sector, the available lands could increase sugarcane production by 73% in relation to current levels. The work has been published in an indexed journal [7].

4 Institutional support received in the period

The e-sensing project is hosted primarily by the Image Processing Division (DPI) of the National Institute of Space Research (INPE), with additional support provided by INPE's Remote Sensing Division (DSR). Both divisions report to the Earth Observation Directorate (OBT). During of the project, INPE gave substantial institutional support to the project as follows:

1. DPI/INPE hired, with additional funds from other projects, a full-time post-doc researcher (Dr. Eduardo Llapa) who is 100% dedicated to the project.
2. DPI/INPE also hired, with additional funds from other projects, a project support person (Ms. Denise Nascimento) who provides essential support for project management.
3. DPI/INPE also provides the IT infrastructure for hosting the data servers bought by the project with support from FAPESP, and for hosting the project's website (http://www.esensing.org).

The institutional support we received from INPE is very good and fulfills the needs of the project.

5 Data management policy

We are following the policy we stated in the project proposal, as follows:

> *Our policy will be to deal with the databases and software created by this project as a resource to be shared with the Brazilian Earth Observation community. Thus, we will open the database after month 24 of the project to the community. We will encourage scientists to develop new data analysis methods and to use the methods and algorithms we will build to develop new applications. We will maintain the database accessible and updated for long-term use by the scientific community.*

Following this commitment, we took the following actions:

a) The images used in the development of the project have been made openly and freely available in the "Earth on AWS" environment in Amazon, as described in Section 3.1 above;
b) The in situ data used for the work on Mato Grosso (section 3.3.2) is openly available in the PANGAEA repository (DOI: 10.1594/PANGAEA.881291).
c) The in situ data related to Campo Verde and Luis Eduardo Magalhaes crop information is being made available in the PANGAEA repository.

6 Papers, Software and Data Published

6.1 Papers Published in Indexed Journals

1. VICTOR MAUS, GILBERTO CÂMARA, EDZER PEBESMA, MARIUS APPEL. dtwSat: Time-Weighted Dynamic Time Warping for Satellite Image Time Series Analysis in R. *Journal of Statistical Software*, 88(5), 2019. DOI: 10.18637/jss.v088.i05.

2. ADELINE MACIEL, GILBERTO CÂMARA, LÚBIA VINHAS, MICHELLE PICOLI, RODRIGO BEGOTTI, LUIZ ASSIS. Spatiotemporal interval logic for reasoning about land use change dynamics. *Inter. Journal of Geographical Information Science*, 33(1):176-192, 2019. DOI: 10.1080/13658816.2018.1520235.

3. MICHELLE PICOLI, GILBERTO CAMARA, IEDA SANCHES, ROLF SIMÕES, ALEXANDRE CARVALHO, ADELINE MACIEL, ALEXANDRE COUTINHO, JULIO ESQUERDO, JOÃO ANTUNES, RODRIGO BEGOTTI, DAMIEN ARVOR, CLAUDIO ALMEIDA. Big Earth Observation Time Series Analysis for Monitoring Brazilian Agriculture. *ISPRS Journal of Photogrammetry and Remote Sensing*, 145 (Nov):328-339, 2018. DOI: 10.1016/j.isprsjprs.2018.08.007.

4. HILTON SILVEIRA, LENIO GALVAO, IEDA SANCHES, IEDO SÁ, TATIANA TAURA. Use of MSI/Sentinel-2 and airborne LiDAR data for mapping vegetation and studying the relationships with soil attributes in the Brazilian semi-arid region. *International Journal of Applied Earth Observation and Geoinformation:* 73 (Dec): 179-190, 2018. DOI:/10.1016/j.jag.2018.06.016

5. SALETE GURTLER, CARLOS SOUZA FILHO, IEDA SANCHES, M. ALVES, W. OLIVEIRA. Determination of changes in leaf and canopy spectra of plants grown in soils contaminated with petroleum hydrocarbons. *ISPRS Journal Of Photogrammetry and Remote Sensing*, 146: 72-288, 2018. DOI: 10.1016/j.isprsjprs.2018.09.011

6. IEDA SANCHES, RAUL FEITOSA, PEDRO DIAS, MARINALVA SOARES, ALFREDO LUIZ, BRUNO SCHULTZ, Campo Verde Database: Seeking to Improve Agricultural Remote Sensing of Tropical Areas. *IEEE Geoscience and Remote Sensing Letters*, 15(3), 2018. DOI: 10.1109/LGRS.2017.2789120.

7. DENISE MARTINI, LUIZ ARAGÃO, IEDA SANCHES, MARCELO GALDOS, CINTHIA SILVA, ELOI DALLA-NORA, Land availability for sugarcane derived jet-biofuels in São Paulo—Brazil. *Land Use Policy* v.70, p. 256-262, 2018. DOI: 10.1016/j.landusepol.2017.10.035.

8. YOALIANG CHEN, DENGSHENG LU, EMILIO MORAN, MATEUS BATISTELLA, LUCIANO DUTRA, IEDA SANCHES, RAMON SILVA, JINGFENG HUANG, ALFREDO LUIZ, MARIA OLIVEIRA. Mapping croplands, cropping patterns, and crop types using MODIS time-series data. *International Journal of Applied Earth Observation and Geoinformation*, 69 (July), p.133-147, 2018. DOI: /10.1016/j.jag.2018.03.005

9. WANDERSON COSTA, LEILA FONSECA, THALES KÖRTING, HUGO BENDINI, RICARDO SOUZA. Spatio-Temporal Segmentation Applied to Optical Remote Sensing Image Time Series. *IEEE Geoscience and Remote Sensing Letters*, v. 15, p. 1-5, 2018. DOI: 10.1109/LGRS.2018.2831914.

10. MARIANE REIS, ISABEL ESCADA, SIDNEY SANT'ANNA, NATHAN VOGT. Towards a Reproducible LULC Hierarchical Class Legend for Use in the Southwest of Pará State, Brazil: A Comparison with Remote Sensing Data-Driven Hierarchies. *Remote Sensing,* v. 9, p. 77, 2017. DOI: 10.3390/land7020065.

11. MARIANE REIS, Luciano DUTRA, ISABEL ESCADA. Examining Multi-Legend Change Detection in Amazon with Pixel and Region Based Methods. *Remote Sensing,* v. 9, p. 77, 2017. DOI:10.3390/rs9010077.

12. FABIEN WAGNER, BRUNO HERAULT, VIVIEN ROSSI, THOMAS HILKER, EDUARDO MAEDA, ALBER SANCHEZ, ALEXEI LYAPUSTIN, LÊNIO GALVÃO, YUJIE WANG, LUIZ ARAGÃO. Climate drivers of the Amazon forest greening. PLOS One, 12(7): e0180932. DOI: 10.1371/journal.pone.0180932.

13. ISAQUE EBERHARDT, BRUNO SCHULTZ, RODRIGO RIZZI, IEDA SANCHES, ANTONIO FORMAGGIO, CLEMENT ATZBERGER, MARCIO MELLO, MARKUS IMMITZER, KLEBER TRABAQUINI, WILLIAM FOSCHIERA, ALFREDO LUIZ, Cloud Cover Assessment for Operational Crop Monitoring Systems in Tropical Areas. *Remote Sensing*, vol.8(3), 2016. DOI:10.3390/rs8030219.

14. MENG LU, EDZER PEBESMA, ALBER SANCHEZ, JAN VERBESSELT. Spatio-temporal change detection from multidimensional arrays: detecting deforestation from MODIS time series. *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 117, pp. 227–236, 2016. DOI: 10.1016/j.isprsjprs.2016.03.00.

15. VICTOR MAUS, GILBERTO CAMARA, RICARDO CARTAXO, ALBER SANCHEZ, FERNANDO RAMOS, GILBERTO QUEIROZ. A time-weighted dynamic time warping method for land use and land cover mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(8): 3729 – 3739, 2016. DOI: 10.1109/jstars.2016.2517118.

16. VIVIAN RENÓ, EVLYN NOVO, ISABEL ESCADA, Forest Fragmentation in the Lower Amazon Floodplain: Implications for Biodiversity and Ecosystem Service Provision to Riverine Populations. *Remote Sensing*, vol. 8, p.886, 2016. DOI: 10.3390/rs8110886.

17. TAÍSE PINHEIRO, ISABEL ESCADA, DALTON VALERIANO, PATRICK HOSTERT, FLORIAN GOLLNOW, Forest degradation associated with logging frontier expansion in the Amazon: the BR-163 region in Southwestern Pará, Brazil. *Earth Interactions*, 20(17):1-26, 2016. DOI: 10.1175/EI-D-15-0016.1.

18. CÉSAR DINIZ, ARLESON SOUZA, DIOGO SANTOS, MIRIAM DIAS, NELTON LUZ, DOUGLAS MORAES, JANAÍNA MAIA, ALESSANDRA GOMES, IGOR NARVAES, DALTON VALERIANO,

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19. BRUNO SCHULTZ, MARKUS IMMITZER, ANTONIO FORMAGGIO, IEDA SANCHES, ALFREDO LUIZ, CLEMENT ATZBERGER. Self-guided segmentation and classification of multi-temporal Landsat 8 images for crop type mapping in southeastern Brazil. *Remote Sensing*, 7:11(14482-14508), 2015. DOI: 10.3390/rs71114482.

20. ISAQUE EBERHARDT, ALFREDO LUIZ, ANTONIO FORMAGGIO E IEDA SANCHES. Detecção de áreas agrícolas em tempo quase real com imagens MODIS (Detection of agricultural areas in near real time using MODIS imagery). *Pesquisa Agropecuária Brasileira*, 50 (7), 605-614, 2015. DOI: 10.1590/S0100-204X2015000700010.

6.2 Papers Published in Brazilian Journals

21. ALBER SÁNCHEZ, LUBIA VINHAS, GILBERTO QUEIROZ, ROLF SIMOES, VITOR;GOMES, LUIZ FERNANDO ASSIS, EDUARDO LLAPA, GILBERTO CAMARA. Reproducible geospatial data science: Exploratory data analysis using collaborative analysis environments. RBC. Revista Brasileira de Cartografia (ONLINE), v.70, p.1844 - 1859, 2018. DOI: 10.14393/rbcv70n5-45036

22. FERREIRA, K. R.; FERLA, L. ; QUEIROZ, G. R. ; VIJAYKUMAR, N. L. ; NORONHA, C. A. ; MARIANO, R. M. ; TAVEIRA, D. ; SANSIGOLO, G. ; GUARNIERI, O. ; ROGERS, T. ; PAGE, M. ; ATIQUE, F. ; MUSA, D. ; SANTOS, J. Y. ; MORAIS, D. S. ; MIYASAKA, C. R. ; ALMEIDA, C. R. ; NASCIMENTO, L. G. M. ; DINIZ, J. A. ; SANTOS, M. C. . A Platform for Collaborative Historical Research based on Volunteered Geographical Information. *Journal of Information and Data Management* - JIDM, v. 9, p. 291-304, 2019.

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26. MARIANE REIS, LUCIANO DUTRA, SIDNEI SANT'ANNA, ISABEL ESCADA. Análise das incertezas envolvidas em classificação multi-legendas da cobertura da terra com suporte de simulação Monte Carlo. *Revista Brasileira de Cartografia*, 69(9):2017.

27. RENNAN MARUJO, LEILA FONSECA, THALES KORTING, HUGO BENDINI, GILBERTO QUEIROZ, LÚBIA VINHAS, KARINE FERREIRA. Remote Sensing Image Processing Functions in Lua Language. *Journal of Computational Interdisciplinary Sciences*, 8(3):163-172, 2017. DOI: 10.6062/JCIS.2017.08.03.0133

28. VINICIUS CAPANEMA, TAISE PINHEIRO, ISABEL ESCADA, SIDNEY SANT'ANNA. Mapeamento de padrões de intensidade da degradação florestal: estudo de caso na região de Sinop, Mato Grosso. RBC. *Revista Brasileira De Cartografia* (Online), v. 70, p. 199-225, 2018. DOI: 10.14393/rbcv70n1-45254.

29. MARCIO AZEREDO, MIGUEL MONTEIRO, ISABEL ESCADA, KARINE FERREIRA, LUBIA VINHAS, TAÍSE PINHEIRO. Mineração de trajetórias de mudança de cobertura da terra em estudos de degradação florestal. *Revista Brasileira de Cartografia*, 68(4): 717-731, 2016.

30. ANDERSON SOARES, THALES KÖRTING, LEILA FONSECA. Improvements of the divide and segment method for parallel image segmentation. *Revista Brasileira de Cartografia*, v. 68(6), p. 1113-1122, n. 2016.

31. BRUNO SCHULTZ, ANTONIO FORMAGGIO, IEDA SANCHES, ISAQUE EBERHARDT, ALFREDO LUIZ, CLEMENT ATZBERGER. Classificação orientada a objetos em imagens multitemporais LANDSAT aplicada na identificação de cana-de-açúcar e soja. *Revista Brasileira de Cartografia*, v. 68(1), pp. 131-143, 2016.

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34. ALANA NEVES, HUGO BENDINI, THALES KÖRTING, LEILA FONSECA, Combining time series features and data mining to detect land cover patterns: A case study in northern Mato Grosso state, Brazil. RBC. *Revista Brasileira de Cartografia* v. 68(6): 1133-1142, n. 2016.

6.3 Data Sets Submitted to Public Repositories

35. Gilberto Câmara, Michelle Picoli, Rolf Simoes, Adeline Maciel, Alexandre Carvalho, Alexandre Coutinho, Julio Esquerdo, João Antunes, Rodrigo Begotti, Damien Arvor (2017): Land cover change maps for Mato Grosso State in Brazil: 2001-2016, links to files. *PANGAEA*, https://doi.org/10.1594/PANGAEA.881291

6.4 Software Packages Developed

36. ROLF SIMÕES, GILBERTO CÂMARA, ALEXANDRE CARVALHO, VICTOR MAUS. SITS: Satellite Image Time Series Analysis. R package available at https://github.com/e-sensing/sits.

37. LUIZ ASSIS, GILBERTO RIBEIRO, VICTOR MAUS. wtss: An R Client for a Web Time-Series Service. Available at https://CRAN.R-project.org/package=wtss

38. ADELINE MACIEL, lucC: Land Use Change Calculus. R package available at https://github.com/ammaciel/lucC.

6.5 Peer-Reviewed Papers in International Scientific Conferences

39. LORENA SANTOS, KARINE FERREIRA, MICHELLE PICOLI, GILBERTO CAMARA. Self-Organizing Maps in Earth Observation Data Cubes Analysis. In: 13th International Workshop on Self-Organizing Maps and Learning Vector Quantization, Clustering and Data Visualization (WSOM+ 2019), Barcelona, Spain, June 26-28, 2019.

40. LORENA SANTOS, ROLF SIMOES, KARINE FERREIRA, GILBERTO QUEIROZ, GILBERTO CAMARA, RAFAEL SANTOS, Clustering Methods to Asses Land Cover Samples of MODIS Vegetation Indexes Time Series. In: 17th International Conference on Computational Science and Applications (ICCSA 2017). Lecture Notes in Computer Science LNCS 10409, pp. 662–673, 2017. DOI: 10.1007/978-3-319-62407-5 48.

41. GILBERTO CAMARA, GILBERTO QUEIROZ, LÚBIA VINHAS, KARINE FERREIRA, RICARDO CARTAXO, ROLF SIMÕES, EDUARDO LLAPA, LUIZ ASSIS, ALBER SANCHEZ. "The e-Sensing architecture for big Earth observation data analysis". Proceedings of the 2017 conference on Big Data from Space (BiDS 17). P. Soille and P.G. Marchetti (eds.). Toulouse, France, December 2017.

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6.7 Papers Presented in International Scientific Conferences

115. ROLF SIMÕES, GILBERTO CÂMARA, ALEXANDRE CARVALHO, GILBERTO QUEIROZ, "Machine Learning Techniques for Dense Satellite Image Time Series Analysis". Presented at 2018 GEO Data Providers Workshop, Frascati, May 2018.

6.8 Doctoral Dissertations

116. PEDRO DIAZ. Crop recognition in tropical regions based on spatio-temporal conditional random fields from multi-temporal and multi-resolution sequences of remote sensing images. 2019. PhD in Electrical Enginnering, PUC-RIO. Advisors: Raul Feitosa, IEDA SANCHES.

117. HUGO BENDINI. Agricultural land classification based on phenological information from high-spatial resolution satellite image time series in the Brazilian Cerrado. 2018. PhD in Remote Sensing, INPE. Advisor: THALES SEHN KÖRTING.

118. MÁRCIO AZEREDO. Mineração e análise de trajetórias de mudança de cobertura da terra: explorando padrões comportamentais no contexto da degradação florestal. Doctoral dissertation in Applied Computing, INPE, 2017. Advisors: ISABEL ESCADA, MIGUEL MONTEIRO.

119. ADELINE MACIEL, Spatiotemporal Interval Logic for Reasoning About Land Use Change Dynamics. Doctoral dissertation in Earth System Science, INPE 2017. ADVISORS: LUBIA VINHAS, GILBERTO CÂMARA.

120. VIVIAN FRÓES RENÓ, Várzeas Amazônicas: Alterações da Paisagem e seus Impactos na Provisão de Serviços Ecossistêmicos e Bem-estar de Comunidades Riberinhas. Doctoral dissertation in Earth System Science, INPE 2016. ADVISOR: ISABEL ESCADA.

121. VAGNER LUÍS CAMILOTTI, Uso e Importância de Recursos Florestais Extrativistas em Comunidades Rurais na Amazônia e suas Relações com Aspectos Socioeconômicos Locais e Características da Paisagem. Doctoral dissertation in Earth System Science, INPE 2016. Advisor: ISABEL ESCADA.

122. VICTOR MAUS, Land use and land cover monitoring using remote sensing image time series. Doctoral dissertation in Earth System Science, INPE 2016. Advisor: GILBERTO CAMARA.

123. TAÍSE PINHEIRO. *Padrões e trajetórias de degradação florestal em fronteiras madeireiras da amazônia* (Patterns and trajectories of forest degradation in the logging frontiers in Amazonia). Doctoral dissertation in Earth System Science, INPE. Viva: 17.12.2015. Advisor: ISABEL ESCADA.

6.9 Master Thesis

124. LUCAS ALENCAR. Dinâmica dos padrões de desmatamento na Amazônia e implicações para o estado de conservação das paisagens. 2018. Dissertação (Mestrado em Ciências de Florestas Tropicais) - INPA. Coorientador: ISABEL ESCADA.

125. LUIS MAURANO. Avaliação da qualidade do mapeamento do desmatamento do projeto Prodes na Amazônia Legal brasileira: estimativa e regionalização dos erros e acertos da classificação. 2018. Dissertação (Mestrado em Sensoriamento Remoto) - INPE. Orientador: ISABEL ESCADA.

126. LIDIANE COSTA. Trajetórias de mudanças de uso e cobertura da terra e estimativas de perda de solo em uma região de expansão agrícola na Amazônia: a bacia do rio Curuá-una, PA. 2018. Dissertação (Mestrado em Sensoriamento Remoto) – INPE. Advisor: ISABEL ESCADA.

127. BRUNO MONTIBELLER. Caracterização espectro-temporal de culturas agrícolas com base em dados de sensores orbitais de média resolução espacial. 2018. MSc in Remote Sensing, INPE. Advisor: IEDA SANCHES.

128. HILTON SILVEIRA. Uso de dados do sensor MSI/Sentinel-2 e de lidar aerotransportado para mapeamento de fitofisionomias de caatinga e estudo das relações com atributos físico-químicos dos solos. 2018. MSc in Remote Sensing, INPE. Advisor: IEDA SANCHES.

129. MIKHAELA PLETSCH. Mineração de informações de imagens de sensoriamento remoto. 2018. MSc in Remote Sensing, INPE. Advisor:: THALES SEHN KÖRTING.

130. THALES VAZ PENHA. Detecção de áreas queimadas utilizando imagens multi-sensores de média resolução espacial, técnicas de GEOBIA e mineração de dados na Amazônia brasileira. 2018. MSc in Remote Sensing, INPE. Advisor:: THALES SEHN KÖRTING.

131. DAYANNA TEODORO QUIRINO. Estimativa da produtividade potencial da cana-de-açúcar em função de imagens de satélite. 2017. Msc in Agronomy, Federal University of Goiás. Advisor: IEDA SANCHES

132. VINICIUS CAPANEMA. Fatores de Degradação Florestal Atuantes em diferentes estágios da fronteira agropecuária na Amazônia: Estudo de caso na região de Sinop, MT. 2017. MSc in Remote Sensing. INPE 2017. Advisor: ISABEL ESCADA.

133. ALANA KASAHARA NEVES. Mineração e dados de sensoriamento remoto para detecção e classificação de áreas de pastagem na Amazônia Legal. 2017. MSc in Remote Sensing. INPE 2017. Advisor: THALES KÖRTING.

134. ANIELLI ROSANE DE SOUZA, Economia e Natureza: Padrões de Uso e Cobertura da Terra Associados a Atividades Agropecuárias e Extrativistas de Comunidades do Sudoeste do Pará. MSc in Remote Sensing, INPE 2016. Advisor: ISABEL ESCADA.

135. ANA CAROLINA MOREIRA PESSOA. Caracterização espectral de estágios sucessionais de fragmentos de Floresta Ombrófila Densa no Domínio Mata Atlântica em imagens TM/Landsat 5. 2016. MSc in Remote Sensing, INPE. Advisor: IEDA SANCHES.

ANNEXES (IN PORTUGUESE)

Relatório sucinto de utilização de recursos da reserva técnica e benefícios complementares

1. Relatórios de Bolsas de Treinamento Técnico
   - 1.1 Luiz Fernando Ferreira Gomes de Assis - 2015/19540-0 e 2016/16555-0
   - 1.2 Alber Hamersson Sánchez Ipia - 2016/03397-7
   - 1.3 Adeline Marinho Maciel – 2017/17529-5
   - 1.4 Heloisa Musetti Ruivo – 2018/03769-7
2. Relatórios Científicos dos Bolsistas de Pós-Doutorado
   - 2.1 Michelle Cristina Araújo Picoli – 2016/23750-3 e 2017/19812-6
   - 2.2 Rodrigo Anzolin Begotti – 2016/16968-2
3. Relatório Científico de Bolsistas de Doutorado
   - 3.1 Rennan de Freitas Bezerra Marujo - 2016/08719-2

ANEXO 1

RELÁTORIO SUCINTO DE UTILIZAÇÃO DE RECURSOS DA RESERVA TÉCNICA E BENEFÍCIOS COMPLEMENTARES EM 2018

(Obs: Os papers mencionados estão disponíveis no site www.e-sensing.org)

Reserva Técnica

Os recursos da reserva técnica do projeto foram utilizados para cobrir a seguinte despesa:

Material de Consumo: Compra de toner para impressora do projeto.

Benefícios Complementares

Os recursos dos Benefícios Complementares do projeto foram utilizados para cobrir as seguintes despesas:

Pesquisador Gilberto Câmara

a) Diárias para Roma - Participação com apresentação na "International Conference on Working Across Sectors to Halt Deforestation and Increase Forest Area", em fevereiro de 2018. O artigo apresentado foi uma versão preliminar do artigo "Big Earth Observation Time Series Analysis for Monitoring Brazilian Agriculture" [3].
b) Diárias para Berlim - Visita técnica à Universidade Humboldt, Berlim, com palestra sobre os resultados do projeto temático "e-sensing", em Março de 2018. O artigo apresentado foi uma versão preliminar do artigo "Big Earth Observation Time Series Analysis for Monitoring Brazilian Agriculture" [3].
c) Diárias para Frascati - Apresentação do trabalho " Machine Learning Techniques for Dense Satellite Image Time Series Analysis" no 2018 GEO Data Providers Workshop, em maio de 2018 [115].

Pesquisador Leila Fonseca

Serviços de Terceiros: Pagamento de revisão de inglês e publicação de três artigos relacionados ao projeto, para fins de publicação internacional.

a) "TerraClass and MapBiomas data assessment: legend and map agreement analysis for the Brazilian Amazon biome" [57]
b) " Segmentation of optical remote sensing images for detecting homogeneous regions in space and time " [58]
c) "Agricultural land classification based on phenological information from high-spatial resolution satellite image time series in the Brazilian Cerrado"[117].
d)