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ORBITAL SENSORS DATA APPLIED TO VEGETATION STUDIES

Dados de Sensores Orbitais Aplicados a Estudos de Vegetação

Yosio Edemir Shimabukuro & Flávio Jorge Ponzoni

Instituto Nacional de Pesquisas Espaciais – INPE

Divisão de Sensoriamento Remoto – DSR

Av. dos Astronautas, 1758, São José dos Campos, SP, 12227-010

yosio@dsr.inpe.br; flavio@dsr.inpe.br

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ABSTRACT

This work presents the contribution of orbital sensors for obtaining information on vegetation studies. Initially it is described the basic concepts of getting information from remote sensors, information about natural resources satellites and their sensors and applications in the study of vegetation. Following it is presented a description of the works using data from orbital sensors for mapping and monitoring vegetation and works for assessment of vegetation biophysical parameters. In addition data from some sensors and products derived from such data like the vegetation indices that have been used for several studies of vegetation cover are presented. In this manner, it is possible to demonstrate the contribution of orbital sensors data especially for mapping and monitoring vegetation cover. The availability of data from new sensors with better spectral, spatial, and temporal characteristics will enable to monitor these resources with more detail to assure quality and sustainability in our planet.

Keywords: Remote Sensing, Forest Cover, Biophysical Parameters, Mapping, Monitoring.

RESUMO

Este trabalho apresenta a contribuição dos sensores orbitais para a obtenção de informações para o estudo de vegetação. Inicialmente são descritos os conceitos básicos de obtenção de informações de sensores remotos, informações sobre satélites de recursos naturais e seus respectivos sensores, e sobre aplicações no estudo da vegetação. A seguir é feita uma descrição dos trabalhos utilizando dados de sensores orbitais para o mapeamento e monitoramento de vegetação e trabalhos de estimativa de parâmetros biofísicos da vegetação. Além disso, são apresentados dados de alguns sensores e produtos derivados desses dados como os índices de vegetação que vem sendo utilizados em vários estudos da cobertura vegetal. Dessa maneira, é possível comprovar a contribuição dos dados de sensores orbitais especialmente no mapeamento e no monitoramento da cobertura vegetal. A disponibilidade de dados de novos sensores orbitais com melhores características espaciais, espectrais e temporais permitirá o monitoramento desses recursos de forma cada vez mais detalhada, para garantir a qualidade e a sustentabilidade no nosso planeta.

Palavras chaves: Sensoriamento Remoto, Cobertura Florestal, Parâmetros Biofísicos, Mapeamento, Monitoramento.

1. INTRODUCTION

The application of remote sensing technology sometimes is misunderstood as a simple data processing or data interpretation task. Frequently professionals involved with remote sensing applications assume that the available data for their studies are a strong and deep expression of a single “truth” and, as a consequence, the generated results are unquestionable. Actually, any result is one of the possible results that could be achieved according to the phenomena studied and the methodological strategy adopted. It is important to remember that remote sensing is dependent on an interaction process between the electromagnetic radiation (REM) and a specific target. The result of part of that interaction process is “translated” or recorded by sensors that present specific capacities in spectral, radiometric, temporal and spatial domains.

Any remote sensing data set is, in fact, a translation product from which results and conclusions have been based on. So, it is important taking into account the history of the data collection, the physical aspects related to the mentioned interaction process and to fully understand the sensor characteristics that generated the data in which the study is based on.

Specifically in vegetation studies the data collection procedure can be carried out at leaf (in-lab or at field conditions) or at canopy levels (in-lab, field conditions, airborne and orbital levels). Independent on the acquisition level, the data set is generated by one or by several sensors that translate the REM x vegetation interaction process according to their own capacities. So, at each acquisition level there will be different ways to translate a single “truth” and it has to be taken into account by the data interpreter. In this work the orbital level approach will be discussed.

Vegetation is one of the most studied targets in remote sensing. The term “vegetation” can be understood by several ways, including botanical, physiological, environmental, physiognomic and agricultural meanings. Independent on the meaning assumed or explored, vegetation can be evaluated or studied at different approaches including spectral characterization of detached leaves (in-lab or at field conditions), physiognomic mapping (thematic mapping), spectral characterization of different canopies and biophysical parameters quantification. So, “vegetation” actually can be understood as a

single leaf or as a complex forest or agricultural crop canopy.

Thinking on a single leaf, its spectral characterization can provide relevant information about plant stress, nutritional and environmental conditions, healthy status etc. It is conducted by radiometric data collected in-lab or at field conditions using radiometers running at straight and numerous spectral bands. These measurements are frequently correlated to chemical and structural leaf data and the results are valid at a specific data collection scale.

The most popular and usual remote sensing application to vegetation studies explores a qualitative approach in which vegetation canopies are identified and geographically represented based on their physiognomic, structural or phenological differences. Here, the spatial remote sensing data characteristics assume great importance since they strongly influence the potential vegetation differentiation.

Since the beginning of the nineties until the present days the so called remote sensing “quantitative” approach has been proposed by several researchers in order to provide scientific information for supporting climate change agendas such as CO₂ emission estimation caused by deforestation (DEFRIES et al., 2002).

These possible approaches have been performed based on the available portable, airborne or orbital sensors data whose technical characteristics actually influence their application results.

In this context, the objective of this work is to present the main aspects related to orbital sensors data characteristics and their applications to vegetation studies.

2. RADIOMETERS APPLIED TO LEAF SPECTRAL CHARACTERIZATION

The spectral characterization of leaves has been reported by several authors even before the common usage of the remote sensing term at the end of the sixties. At that time, researchers were excited by the orbital remote sensing possibilities that would be available at the beginning of the seventies. Then the intuitive and dominant idea about the main usage of the spectral characterization of vegetation would be its direct comparison to orbital radiometric data, e.g., the comparison between these two spectral characterizations levels (in-lab or at field conditions and the orbital).

Currently it is relatively known that this comparison is not trivial and sometimes results achieved at a specific level or scale (leaf, plant or canopy) must be specific at each data acquisition level. Extrapolations include high level of uncertainties and then insisting in the direct comparison mentioned implies on a total waste of time.

Despite of that constraint, the spectral characterization of leaves or other parts of plants can be relevant in different applications such as the evaluation of stress and disease impacts, the estimation of agricultural productivity, etc. Thus, several authors have dedicated great part of their professional life studying the spectral properties of leaves such as Gates et al. (1965) that were the first researchers that described the physical aspects related to the radiometric electromagnetic radiation (REM) x leaves interaction process. Their entire work was carried out in-lab using equipment specially designed for chemical studies, but important details such as data acquisition geometry and experiment set up were omitted.

Gausman et al. (1969) published an important cotton leaves spectral characterization study that emphasized the relationship between leaves reflectance and their internal structure. In this work the experimental set up was a little valorized, but clearly the spectral characterization assumed almost a universal meaning.

Perhaps one of the most didactic publication related to spectral characterization of leaves had been presented by Kumar (1974). It was a report of the research project based on a literature review about radiation from plants, including reflection and emission approaches. The author described a deep discussion about chemical, structural and physiological aspects influencing in the spectral reflectance of leaves. In the last session of this work, the Kubelka-Munk theory proposed in 1931 (KUBELKA and MUNK, 1931) based on the radiative transfer theory was presented as an alternative to explain the REM path through the leaf internal structure.

Nowadays, similar experiments related to leaves spectral characterization include a detailed description of the experiment set up and of the radiometer utilized. Special devices have been developed to minimize the influence of geometrical factors in the leaf reflectance estimation and portable concept has also been incorporated into the

instruments designs. Thus, results from experiments dedicated to the spectral characterization of leaves present a known accomplishment mainly limited to the acquisition data scale.

The most frequently used accessories that have been attached at spectral radiometers to perform spectral characterization of leaves have been the integrating spheres and more recently the Leaf-clip. The main advantage provided by these accessories is the minimization of geometric influence on the radiometric measurements and making possible the fully understanding of leaf spectral behavior, since reflectance, transmittance and absorbance can be measured. Figure 1 shows the integrating spheres and a leaf-clip being used in the spectral characterization of leaves.

Integrating sphere from ASD Spectral Devices Inc. Integrating sphere from LICOR Leaf-clip from ASD Spectral Devices Inc.

3. VEGETATION COVER EVALUATION: MAPPING, MONITORING AND BIOPHYSICAL PARAMETERS ESTIMATION

As mentioned before as soon as aerial photographs or airborne images and orbital images have become available, their first application was mapping vegetation canopies. So, the first concerning was evaluating the potential of these products to identify different types of vegetation canopies in terms of physiognomic and floristic characteristics.

It is important to remember that vegetation canopies can be composed by different species, plants with several and not uniform architectures, diverse spatial arrangements besides changing with time. Phenology and healthy conditions can also influence the canopy spectral characteristics given to the temporal aspect with crucial importance. Thus, the application of remote sensing data for identification of vegetation canopy types has to include spatial, spectral and temporal domains.

Orbital sensors have been the most important instruments from which vegetation mapping has been improved. They present specific spatial, spectral, radiometric and temporal capacities that have to be taken into account according to the canopy under evaluation. Matching sensor characteristics and vegetation mapping objectives is one important step of the entire vegetation study that must be fully concluded to guarantee the well succeeded task.



Fig. 1 – The integrating spheres and a leaf-clip being used in the spectral characterization of leaves.

Boyd and Danson (2005) presented a good intellectual reflection about the application of orbital remote sensing to forest resources evaluation. The authors have considered the last three decades of research development in this specific remote sensing application focusing on three levels of information, namely: 1) the spatial extent of forest cover, which can be used to assess the spatial dynamic of forest cover; 2) forest types; and 3) biophysical and biochemical properties of forests. Thus it is possible to realize clearly also three possible approaches: vegetation mapping, floristic identification and biophysical and/or biochemical data quantification.

The same authors have presented a timeline depicting launch date of some satellites and platforms operating in the optical and radar spectrum affording the collection of forest resources information. This timeline is presented on Figure 2.

As can be seen, the orbital payloads of the past decades have been based on two broad types of sensor systems: the optical and active Synthetic Aperture Radar (SAR) systems. The optical systems have run from 400nm to 3000nm wavelength range whereas the microwave systems at wavelengths between 1cm and 100cm. That wavelength size difference influences the canopy information nature that can be extracted from the generated images. Optical wavelengths are several orders of magnitude smaller than the leaves, needles and branches that make up a forest canopy and, consequently, radiation may be both absorbed and scattered by these components. For longer microwave wavelengths, scattering from leaves, branches, trunks and the ground is the dominant mechanism (BOYD and DANSON, 2005). So, it is expected that from optical data the information on the amount of foliage and its biochemical properties can be extracted whereas microwave systems can provide information on woody biomass and canopy structure.

Danson (1995) mentioned that extracting information of forest resources therefore depends on developing techniques to infer the desired resource information from the remotely sensed data acquired by various satellite systems that have been in operation. Lambin (1999) agreed that different orbital systems and techniques have been developed for different forest ecosystem and resource requirements.

3.1 Vegetation mapping: canopy extent and dynamics

In a world wide term vegetation mapping has focused both agricultural and forestry assessments. The first one (agricultural) has also been included in the so called “land use” mapping and its dynamic has been associated to crop growing (phenology), health conditions and harvest estimations. Forestry assessment relies on the delineation of forest from non-forest and the calculation of the areal extent of forest cover (BOYD and DANSON, 2005), besides including the identification and quantification of impacts on forests, such as fire, inundation and deforestation activities.

Townshend and Justice (1988) mentioned that the utility of a particular orbital system to map forest and non-forest classes is dependent upon the size of the deforested areas under study, their spatial arrangement and the spectral contrast between the deforested areas and the original forest. Frequently fine spatial resolution sensors provide accurate estimates of forest and non-forest classes, but when extent areas have to be evaluated and such images are not available to the entire region, extrapolation of results may be inaccurate. It has been particularly true at regional and global levels by the relatively high costs involved in the high resolution images acquisition. Malingreau and Tucker (1988) have also emphasized the low frequency of high resolution

Year	Satellite (Main sensors carried on board)
1972	ERTS-1 (later renamed as Landsat-1) (MSS)
1975	Landsat-2 (MSS)
1978	Landsat-3 (MSS)
1979	NOAA-6 (AVHRR)
1981	NOAA-7 (AVHRR)
1982	Landsat-4 (MSS, TM)
1983	NOAA-8 (AVHRR)
1985	Landsat-5 (MSS, TM); NOAA-9 (AVHRR)
1986	SPOT-1 (HRV); NOAA-10 (AVHRR)
1988	NOAA-11 (AVHRR); IRS-1A (LISS I, LISS II)
1990	SPOT-2 (HRV)
1991	NOAA-12 (AVHRR); ERS-1 (ATSR, SAR); IRS-1B (LISS I, LISS II)
1992	JERS-1 (SAR, OPS)
1993	SPOT-3 (HRV)
1994	NOAA-14 (AVHRR)
1995	ERS-2 (ATSR, SAR); IRS-1C (LISS III); Radarsat (SAR)
1997	IRS-1D (LISS III); SeaStar (SeaWiFS)
1998	SPOT-4 (HRVIR, Vegetation); NOAA-15 (AVHRR)
1999	Landsat-7 (ETM+); IKONOS (High resolution sensors); Terra (MODIS, MISR, ASTER)
2000	NOAA-16 (AVHRR); EO-1 (Hyperion, ALI); EROS A1 (EROS A1)
2001	Quickbird-2 (High resolution sensors); PROBA (CHRIS)
2002	SPOT-5 (HRG); Envisat (AATSR, ASAR, MERIS); AQUA (MODIS); NOAA-17 (AVHRR)
2003	ICESat (GLAS)
	Radarsat-2 (SAR)
	ALOS (VSAR, AVNIR-2)
	NASA (VCL)

Figure 2 – Launch date of some satellites and platforms operating in the optical and radar spectrum affording the collection of forest resources information (BOYD and DANSON, 2005).

data acquisition compounded further in tropical regions particularly by cloud cover and smoke from forest fires. To overcome some of these limitations, data from coarse and moderate spatial resolution optical and SAR sensors have been used. The first ones have been represented by the Advanced Very High Resolution Radiometer (AVHRR), Envisat Medium Resolution Imaging Spectrometer (MERIS) and Moderate Resolution Imaging Spectroradiometer (MODIS).

Synergy of remote sensed data from multiple sensors has been shown to provide improved delineation of forest and non-forest classes and it allows for the exploitation of exclusive information on the forest and non-forest provided by different spectral data collected by different sensors (BOYD and DANSON, 2005). Following that possibility Kuplich et al. (2000) explored an interesting approach combining SAR data with those acquired by optical sensors.

Other attractive synergy can be experienced by combining sensors with different spatial resolution

in order to access texture information from canopies that is a result of the canopy complexity in terms of its spatial (vertical and horizontal) structure.

Choosing both the source data (sensor or sensors) and the strategy (methodology) that will be adopted in vegetation mapping is dependent on several aspects such as the mapping objectives, extent of the mapping area, vegetation dynamic (phenology or human impact), costs involved, personal knowledge, and available time to perform the mapping activity. The most important aspect then is to maintain as much as possible the compatibility between the sensor data characteristics and the desired information to be extracted.

3.2 Floristic identification: vegetation type

Vegetation type identification through orbital remote sensed data has been one of the most desired applications due to its economical, academic and social relevance. Despite that strong justification, the ever present ambiguity on the remote sensed data and the dynamic characteristics of the vegetation canopies become that identification a hard task.

Once again taking into account agricultural applications, the crop species identification sometimes is carried out with relative easiness. Spatial, spectral and temporal domains are quite important in that identification, but different data aggregation (such as agricultural calendar, field information, etc.) is also an important aspect to be considered by the professionals involved.

In forestry applications there are many examples of forest type identification and mapping using remotely sensed data acquired by both optical and SAR sensors in temperate regions (Boyd and Danson, 2005). However, in tropical regions the heterogeneity of forest cover types and the highly complex spectral response from them have limited the actual possibilities.

The effective inclusion of temporal domain has guaranteed a sensitive improvement in the vegetation type identification due to the exploitation of temporal changes in spectral response from different vegetation types as a result of phenological activity (leaf shedding, canopy greenness and senescence).

Knowing the ecological requirements of specific species frequently allows previewing or estimating their occurrence on a specific environmental condition that may be identified from remotely sensed data. In this case we are doing an

indirect species identification rather than doing that by its spectral signature or canopy image pattern.

3.3 Canopy biophysical and biochemical properties: quantitative approach

Accessing both biophysical and biochemical information from canopies may be one of the most valuable application of remote sensing data. Actually it represents a higher application level since it calls on a deeper technical knowledge from the personal involved. Thus the interaction process between the electro radiometric radiation and vegetation must be fully understood as well as the data acquisition geometry.

The quantitative approach has been valued since intense global change discussions became popular. Variables such as leaf area index (LAI) and leaf biochemistry affect vegetation function in terms of light interception and absorption, nutrient cycling and productivity. According to Running et al. (1989), these biophysical parameters are the key spatial variables required to drive forest ecosystem simulation models at a range of spatial scales and considerable effort has been expended in developing remote sensing techniques to estimate them over extensive vegetated areas.

Chen and Cihlar (1996) considered that the past 30 years has seen the adoption of two approaches to relate remotely sensed data to biophysical variables. In physical modeling, canopy radiative transfer processes are simulated mathematically with valuable insights into the fundamental factors driving the relationships between remotely sensed data and vegetation biophysical and biochemical properties. In spite of being more logical and robust, that physical approach has been hindered by factors such as the canopy heterogeneity, the dynamic characteristics of the canopy optical properties and external effects, such as atmospheric scattering and absorption, which are difficult to model.

The empirical modeling, involving remote sensing data and various transformed products such as vegetation indices and ground-based biophysical and biochemical property data, is calibrated by interrelating known coincident observations of the remotely sensed and ground data (BOYD and DANSON, 2005). Despite the attractiveness of using this approach, there is a lack of appropriate ground data that can be brought together with the remotely sensed data.

Danson (1995) mentioned that of the many types of biophysical property that influence the radiation at optical wavelengths from vegetation, LAI is the most important. Applications in agriculture have been relatively well succeeded since the relationship between LAI and crop productivity (mainly grain production) is almost direct. In forest applications the relationship between LAI and ground biomass or timber volume is weak or inconsistent. Anyway, sensors whose data permit evaluating visible and near infrared dynamic that is evident among different vegetation cover types, theoretically offer good enough data to evaluate canopy biophysical and biochemical properties.

Recently middle infrared or also called short wave infrared (SWIR) has been explored as an important spectral region to estimate LAI. Nemani et al. (1993) found that incorporating SWIR from TM/Landsat 5 sensor with red and near infrared bands normalized the effect of variable canopy cover on the relationship with LAI. Boyd et al. (1999) revealed by NOAA AVHRR sensor for thermal emission to derive SWIR reflectance, increased the strength of the relationship between radiation acquired in SWIR wavelengths and total forest biomass of west African tropical forests over that obtained using NDVI.

Boyd and Danson (2005) presented another alternative to increase the estimation of forest LAI using optical sensors that has focused on high-spectral resolution data, where measurements of surface radiance are made in several hundred narrow wavebands. Some experiments carried out in the nineties have shown that calculation of first or second derivatives of the canopy reflectance may suppress the effects of variation in understory reflectance allowing a more accurate estimation of LAI, such as mentioned by Gong et al. (1992) and Johnson et al. (1994). Here, sensors such as MODIS, MERIS and EO-1 Hyperion have provided good opportunities to apply the techniques based on high-spectral resolution data to estimate vegetation biophysical properties.

4. REMOTE SENSING DATA

As mentioned above since the beginning of orbital remote sensing technology application several sensors have been built generating data that have been applied in different approaches. These data include digital numbers (a quantity proportional to

the effective radiance measured by the sensor), radiance, reflectance (frequently Bidirectional Reflectance Factors – BRF) or a variety of indices such as NDVI, EVI, etc.

The nature of the available data is dependent upon both the sensor engineering and the agency responsible for the data distribution. When only digital numbers are distributed, sometimes users have to convert them to physical values, according to their needs and such activity has become quite common nowadays.

Digital numbers have been preferred in qualitative approaches, mainly characterized by mapping and monitoring tasks. In this case, the main need is identifying objects or target categories also called “classes” that are represented by polygons on maps. Here it is mandatory to fully understand the sensor limitations and potentials to permit the identification of those classes established at the legend. Class identification can be performed by visual interpretation, automatic digital classification of a hybrid procedure including both. Mapping procedures can also be carried out using physical values, but any conversion step can introduce radiometric changes, which can prejudice class or classes separation.

Physical values such as radiance or reflectance (BRF) have been utilized more frequently in quantitative studies in which relationships between image radiometry and biophysical and/or geophysical parameters are analyzed. From these kind of data it is possible to spectrally characterize objects, including their temporal spectral changes, calculate other radiometric-based quantities (indices) and evaluate empirically (from regression models) or physically (from radiative transfer models) their relationship with biophysical and/or geophysical parameters.

Mapping through digital numbers or spectrally characterizing land use classes and vegetation types by physical values are activities dependent on the sensor capabilities. Table 1 shows some sensors characteristics that have been explored in vegetation data assessment.

Figure 3, for instance, shows a pair of color composite images generated by CCD/CBERS-2 (left) and the CCD and HRC/CBERS-2 fused image (right).

In spectral terms, Meddens et al. (2011) presented the effect of spatial resolution on the

spectral characterization of some targets as seen in Figure 4. As sensors present differences in spectral, radiometric and temporal domains, similar differences should be expected between spectral characterizations performed by different sensors. Then for mapping purposes even at a visual interpretation approach it is clear that the defined legends should be different according to the images chosen for the work.

We can see that the increase of number of sensors available for the remote sensing community caused the improvement of image processing techniques. Besides digital numbers, radiance, and reflectance values of original spectral bands, the transformed images such as vegetation indices (Moreira and Shimabukuro, 2004) can also be explored in both qualitative and quantitative approaches. The vegetation indices are the most popular radiometric transformation for vegetation assessment.

These indices are based on the spectral characteristics of the vegetation targets in the red (R) and near infrared (NIR) portions of the electromagnetic spectrum (Tucker, 1979). As mentioned before, the vegetation cover presents a high spectral response in the NIR region and low spectral response in the red region. The most used vegetation index is NDVI (Rouse et al., 1973) defined as: $NDVI = (NIR - R) / (NIR + R)$. This index has been used since the 70's especially applied to AVHRR (Advanced Very High Resolution Radiometer) data. As we can see this index is very reliable depending on the quality of radiometric correction of these spectral bands. However this index presents the saturation problem when considering the dense vegetation cover and therefore is not recommended for the Amazon forest assessment.

In general NDVI can be affected by the ground (e.g. soil type) and the atmospheric condition. In this context several derived vegetation indices have been proposed to minimize these effects. SAVI (Soil Adjusted Vegetation Index; Huete, 1988) was proposed for minimizing the soil effects, while ARVI (Atmospheric Resistant Vegetation Index; Kaufman and Tanré, 1992) was proposed for minimizing the atmospheric effects. SAVI is defined as: $SAVI = [(NIR - R) / (NIR + R + L)] * (1 + L)$; and ARVI is defined as: $ARVI = (NIR - R * B) / (NIR + R * B)$, where B is the spectral

Table 1. Characteristics of some orbital sensors of great importance for the vegetation monitoring (Source: Adapted from Shimabukuro et al., 2009).

Sensor	Satellite	Spatial resolution	Temporal resolution	Number of spectral bands
ETM+	Landsat-7	15/30/60 m	16 days	8
TM	Landsat-4/5	30/120 m	16 days	7
MODIS	Terra/Aqua	250/500/1000 m	~ 1 day	36
ASTER	Terra	15/30/90 m	16 days	14
CCD	CBERS	20 m	26 days	5
HRC	CBERS	2,8 m	26 days	1
WFI	CBERS	260 m	5 days	2
HRG	SPOT-5	2,5/10/20 m	26 days	5
Hyperion	EO-1	30 m	16 days	220
SAR	RADARSAT-2	3 to 100 m	24 days	Band C
				HH, HV, VV e VH
ASAR	ENVISAT-1	30 to 1000 m	35 days	Band C
				VV, HH, VV/HH, HV/HH e VH/VV
AWIFS	IRS-P6	56 m	5 days	4
LISS 4	IRS-P6	5,8 m	5 days	3
PALSAR	ALOS	10/20/100 m	45 days	Band L
				HH, HV, VH, VV

response in the blue band; R is the spectral response of red band; NIR is the spectral response of near infrared band; and L is a constant value used for minimizing the soil effect. For MODIS data, it was created a new vegetation index, named Enhanced Vegetation Index (EVI; Huete et al., 1997; Justice et al., 1998) based on SAVI and ARVI concepts: $EVI = G * (NIR - R) / (L + NIR + C1 * R - C2 * B)$, where $L = 1$; $C1 = 6$; $C2 = 7.5$; and $G = 2.5$. Figure 5 shows the NDVI and EVI images for a area located in the Rondônia area, Brazilian Amazon. Table 2 lists several other derived vegetation indices.

Observing the indices formulations presented on Table 2 it is clear that visible, specially red, and near infrared spectral regions are the most frequently explored. Thus, orbital sensors running at these two regions offer potential utility to vegetation information assessment.

5. APPLICATIONS

5.1 Land cover mapping and monitoring

Orbital images offer a great advance in mapping tasks due to both relative extent surfaces imaged comparing to aerial photos, for example, and

the synoptic imagery of the Earth surface. So, several territorial mapping projects have been developed in different scales exploring also different approaches. A good example of a well succeeded mapping project based in orbital images is the Amazonian forest monitoring (PRODES) carried out by the National Institute for Space Research (INPE), Brazil, whose main objective is the annual deforestation rate estimation (INPE, 2002).

PRODES effectively started at the eighties based on the visual interpretation of images of the Thematic Mapper sensor onboard of Landsat 5 satellite (TM/Landsat 5). At that time the TM/Landsat 5 images were distributed in photographic format and at different scales. The PRODES' visual interpretation was based on 1:250.000 scales resulting in 1.2 x 1.2 m photographic images. The result of the visual interpretation was converted to digital format (digitalization) and imported to a GIS from which statistical data were generated.

Nowadays PRODES has been carried out based on a hybrid procedure that includes digital image processing and visual interpretation (Shimabukuro et al., 2000). The digital image processing is basically composed by a spectral

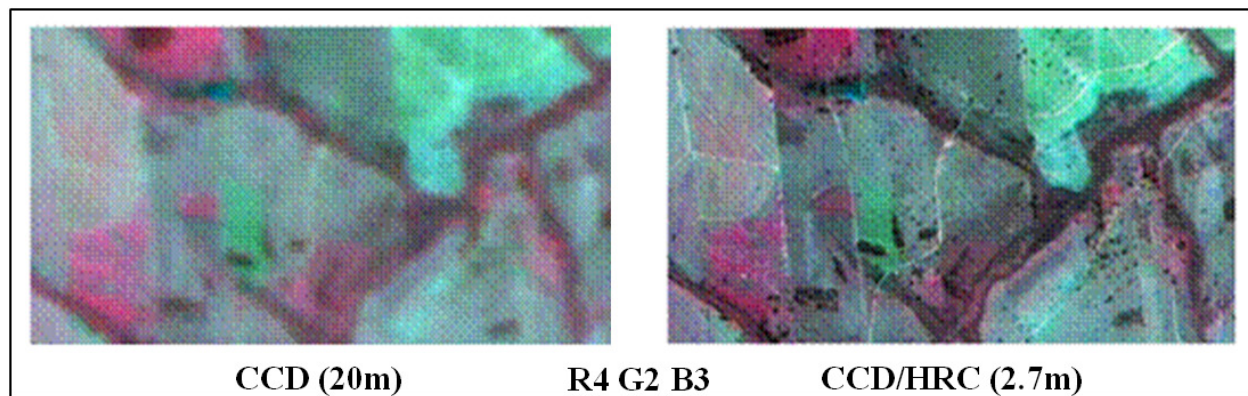


Fig. 3 – CCD/CBERS-2 and CCD and HRC/CBERS-2 fused color composite images from the same Earth surface portion.

mixing modeling application followed by an automatic unsupervised image classification followed by an image edition procedure.

Other important example of orbital images available at digital numbers format application is the Mata Atlântica Forest Remain mapping conducted by Fundação SOS Mata Atlântica and INPE. This project has been carried out since the beginning of the nineties and it is entirely based on the visual interpretation of orbital images from different sensors such as TM/Landsat 5, Enhanced Thematic Mapper Plus of Landsat 7 (ETM+/Landsat 7) and CCD/CBERS 2B.

The DETER project created in 2003 (Shimabukuro et al., 2006) is part of the activities of the Action Plan to prevent and to control deforestation in the Brazilian Amazon, under the responsibility of the Inter-ministerial Permanent Working Group, coordinated by Civil House. It is another example where orbital sensor data has been contributing for detecting deforestation activities in the Amazonia region. It is based on the PRODES Digital methodology using MODIS sensor data. The DETER and PRODES are the complementary projects, i.e., while DETER provides information in a near real time, using moderate spatial resolution images, useful for control policies, PRODES estimates annually the deforested areas.

The Ministry of Environment (Ministério do Meio Ambiente) has tried to map the main Brazilian biomes using TM/Landsat 5 images. This initiative has been called PROBIO and it has been conducted by several Brazilian agencies, including universities and research institutions. The main PROBIO products have been the vegetation maps that cover the entire Brazilian territory. Nowadays the PROBIO results have been reviewed in order to improve some

maps using AVNIR/ALOS images that present better spatial resolution than TM/Landsat 5.

5.2 Estimate of vegetation biophysical parameters

Estimating vegetation biophysical parameters from orbital images radiometry has not been a trivial task, since the reflected radiance from vegetation canopies is not explained by a simple or unique parameter or phenomena. Actually, it is a result of a complex interaction process that frequently can not be explained by simple empirical models such as regression models, then being necessary to adapt radiative transfer models to fully describe it.

Goel (1988) presented a good scientific basis of radiative transfer models applied to simulate the reflectance of vegetation canopies. The author described what he called by “direct” and “inverse” approaches. The direct approach considers that the canopy reflectance can be estimated or calculated by a known input data set. These input data include geometrical (illumination and observation angles), spectral (from the vegetation elements such as leaves, trunks, flowers etc and from soils or litter) and biophysical data. The inverse approach is dedicated to estimate any input data from a reflectance value.

Obviously the inverse approach is more difficult to be carried out since the canopy reflectance can be explained by several input data combinations (ambiguity). Thus, in spite of being more physically consistent the application of radiative transfer models in canopies biophysical data estimation is still rare. Empirical models have been defined considering biophysical data as independent variables and the canopy reflectance as the dependent one.

One of the most important biophysical parameter from canopies that have been estimated

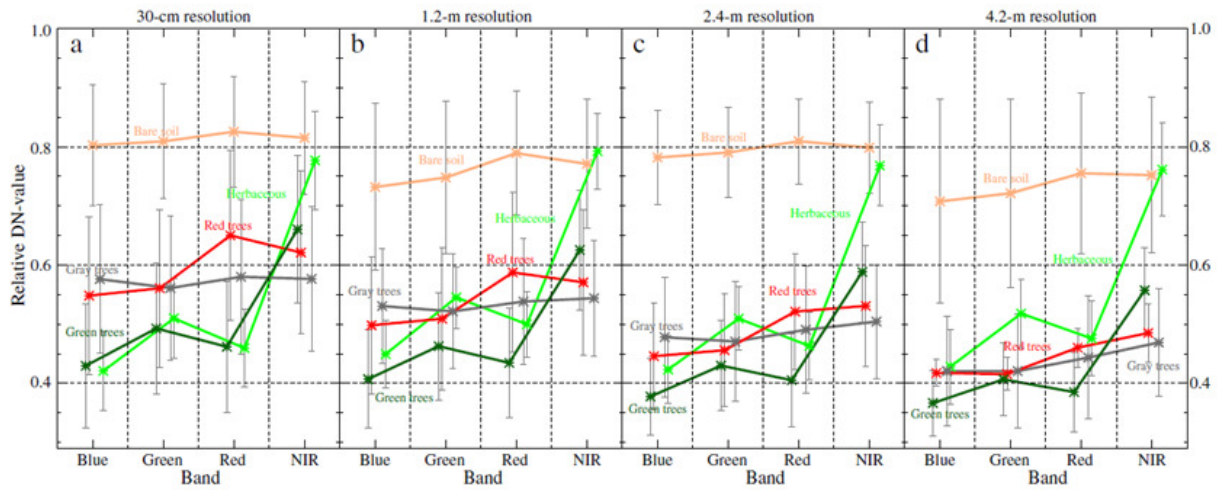


Fig. 4 – Effect of spatial resolution on the spectral characterization of some targets (MEDDENS et al., 2011).



Fig. 5: EVI and NDVI composite (29 Sep – 14 Oct 2000) images over Rondonia region derived from MODIS data.

from orbital sensors data is the Leaf Area Index (LAI). Its estimation by indirect methods can include instrumentation used at field conditions such as hemispherical photography and LAI 2000 (Campoe, 2008) and at airborne or orbital sensors.

The estimation of LAI by airborne or orbital sensors data is dependent on canopy structure that influences the multiple shadowing inside the canopy upper layers. For agricultural crops canopies, for instance, the estimation of LAI from reflectance data present on airborne or orbital images is relatively easy to be done. The same procedure carried out with forest data frequently results in weak or inconsistent estimations.

Sanches et al. (2008) compared estimations of LAI from hemispherical photography and from

monthly LAI estimation of MODIS sensor product for a specific boundary Amazonian/Cerrado forest type. They concluded that the relationship between the hemispherical photography estimations of LAI and those performed from MODIS data was not significant.

Verger et al. (2011) fused MODIS and SPOT Vegetation data and from neural network methodology they estimated LAI that compared to the original MODIS data presented higher correlation coefficients with LAI data collected from field conditions.

The relationship between vegetation indices and LAI has also been evaluated by Wang et al. (2005) that found high correlations between NDVI and LAI. Hasegawa et al. (2009) have proposed a

Table 2 - Vegetation Indices derivates from orbital sensors data.

Vegetation Index	Equation	Reference
Ratio Index	$RI = NIR / R$	Jordan (1969)
Perpendicular Vegetation Index	$PVI = \sin(a)NIR - \cos(a)red$ Where, a: Angle between the soil line and the NIR axis.	Richardson and Wiegand (1977)
	$PVI = \sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2}$ Where, (x1, y1) is the co-ordinate of the pixel and (x2, y2) is the coordinate of soil line point that is perpendicular to pixel co-ordinate.	
Global Environment Monitoring	$GEMI = \eta (1 - 0.25\eta) - (R - 0.125) / (1 - R)$	Pinty and Verstraete (1992)
	$\eta = [2(NIR^2 - R^2) + 1.5NIR + 0.5R] / (NIR + R + 0.5)$	
Transformed Soil-Adjusted Vegetation Index	$TSAVI = a*(R - a*NIR - b) / (R + a*NIR - a*b)$	Baret et al. (1989)
Optimized Soil-Adjusted Vegetation Index	$OSAVI = (1 / a^2 + 1)^{1/2} * (NIR - a*R - b)$	Rondeaux et al., (1996)
Weighted Difference Vegetation Index	$WDVI = NIR - g*R$	Clevers (1988; 1989)
Green Normalized Difference Vegetation Index	$GNDVI = (NIR - G) / (NIR + G)$	Gitelson et al. (1996)
Modified Soil-Adjusted Vegetation Index	$MSAVI = (NIR - R)(1 + L) / (NIR + R + L)$	Qi et al. (1994)

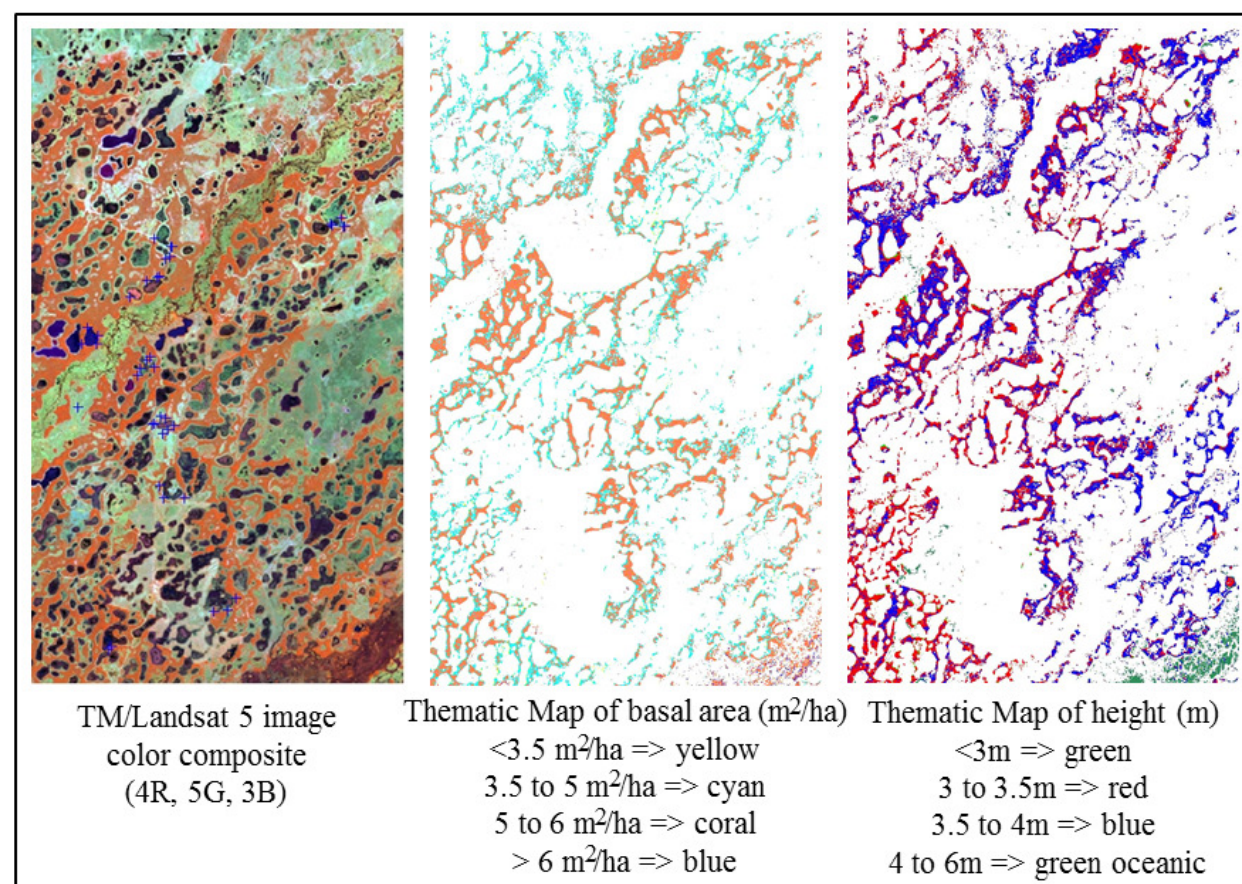


Fig. 6 – Canopy structural parameters estimated from orbital sensor data.

new vegetation index called normalized hotspot-signature Vegetation Index (NHVI) to be correlated to LAI on a boreal forest in Canada. This new vegetation index is calculated from the maximum and minimum BRF values.

The relationship between vegetation indices and LAI has also been evaluated as by Wang et al. (2005) that found high correlations between NDVI and LAI. Hasegawa et al. (2009, 2010) have proposed a new vegetation index called normalized hotspot-signature Vegetation Index (NHVI) to be correlated to LAI on a boreal forest in Canada. This new vegetation index is calculated from the maximum and minimum BRF values.

The canopy structure can also be evaluated from orbital data. Figure 6 shows a sequence of three images. The first one (left) is a TM/Landsat 5 image color composite (4R, 5G, 3B) of a small part of Pantanal region in Brazil. The two other images are actually representative of two structural parameters frequently utilized by foresters such as Basal area (G) and the standard deviation of the total tree height (R).

The spatial distribution of G and R was based on their empirical relationship with infrared data (TM/Landsat 5, band 4).

According to Freitas and Shimabukuro (2007) the optical systems most used in forest ground biomass estimation have been IKONOS, Landsat 5 and NOAA. MODIS data of Terra satellite have been utilized to monitor the forest landscape changes. At this last context, orbital images from ALOS/PALSAR, TerraSAR-X and CosmosSKYMED have been used identifying details of that changes (Disperati et al., 2010).

6. GENERAL CONSIDERATIONS

Orbital sensors have been contributing with important information related to location, type and vegetation cover conditions, then being part of any vegetation assessment studies.

Currently, the orbital sensors data has allowed to perform operational projects such as PROBIO, PRODES, DETER and Mata Atlântica Forest Remain projects.

Land cover classification has been possible using coarse, moderate and medium resolution data.

Vegetation biophysical parameters can be mapped using moderate spatial resolution data.

The availability of new sensors with improved spatial, spectral and temporal resolutions allows the

monitoring of vegetation resources in order to secure the life quality in the planet.

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