Revista Brasileira de Cartografia (2014) N⁰ 66/7 - International Issue: 1517-1529
Sociedade Brasileira de Cartografia, Geodésia, Fotogrametria e Sensoriamento Remoto
ISSN: 1808-0936

MULTI-RESOLUTION IN REMOTE SENSING FOR AGRICULTURAL MONITORING: A REVIEW

Múltiplas Resoluções do Sensoriamento Remoto Aplicado à Agricultura: uma Revisão

Jurandir Zullo Junior[1], Priscila Pereira Coltri[1], Renata Ribeiro do Valle Gonçalves[1] & Luciana Alvim Santos Romani[2]

[1]Universidade Estadual de Campinas – UNICAMP
Centro de Pesquisas Meteorológicas e Climáticas Aplicadas a Agricultura - CEPAGRI
Cidade Universitária "Zeferino Vaz" - Campinas/SP 13083-970
{jurandir; pcoltri; renata}@cpa.unicamp.br

[2] Empresa Brasileira de Pesquisa Agropecuária – EMBRAPA
Embrapa Informática Agropecuária
Av. André Tosello, nº 209 Campus da Unicamp, Barão Geraldo Caixa Postal: 6041 CEP: 13083-886 - Campinas - SP
luciana.romani@embrapa.br

Recebido em 30 de Julho, 2014/ Aceito em 26 de Agosto, 2014
Received on July 21, 2014/ Accepted on August 26, 2014

ABSTRACT

We present a review of literature on remote sensing spatial and temporal images resolution applied to agriculture purposes. In this paper, the definitions are reviewed and a focus is given on the applications of resolutions in agricultural studies. A few main applications with low, medium and high spatial resolution focus were selected for this review, especially in sugarcane and coffee crops, where remote sensing contributions are traditionally important. The paper starts with an overview of agriculture and remote sensing, focused on the history of spatial and temporal resolutions uses. This section is followed by a review of low spatial and high temporal resolution systems, with important results in sugarcane. In this section studies conclude that sensors like AVHRR/NOAA can significantly contribute to improve sugarcane monitoring, as well as help understanding of development and expansion. After that, we present medium and high spatial resolution systems, especially for coffee crops that have been showing good results in fine scale, with detailed information. Studies conclude that satellites like Geoeye and IKONOS can obtain biophysical information of the culture and satellites like Landsat can monitor the coffee growing. Finally the review presents a conclusion with some key recommendations.

Keywords: Sugar-cane, Coffee, Spatial Resolution, Temporal Resolution, Remote Sensing.

RESUMO

Uma revisão de literatura em resoluções espacial e temporal é apresentada nesse artigo focando a aplicação do sensoriamento remoto em agricultura. Inicialmente, definições são revisadas e considerações são feitas às aplicações de diferentes resoluções em estudos com agricultura. As principais aplicações com baixa, média e altas resoluções espaciais foram selecionadas para essa revisão, especialmente nas culturas de cana-de-açúcar e café, onde o sensoriamento remoto tem uma contribuição tradicional. O artigo apresenta uma revisão em agricultura e sensoriamento remoto, focando na história da utilização das resoluções espaciais. Também inclui uma revisão em baixa resolução espacial e alta resolução temporal com resultados importantes para a cultura da cana-de-açúcar, mostrando que satélites como o AVHRR/NOAA podem contribuir significativamente para aprimorar o monitoramento da cana-de-açúcar, assim como entender seu desenvolvimento e expansão. Uma revisão em sistemas de média e alta resolução espacial, especialmente na cultura do café, que tem apresentado ótimos resultados com dados de fina escala e informações detalhadas, é apresentada. Estudos concluem que satélites como o Geoeye e IKONOS podem obter informações biofísicas da cultura e satélites como o Landsat podem monitorar o crescimento do café.

Palavras chaves: Cana-de-açúcar, Café, Resolução Espacial, Resolução Temporal, Sensoriamento Remoto.

1. INTRODUCTION

The beneficial use of remote sensing for agricultural crop monitoring has been known as early as 1929 when aerial photography was used to map soil resources (Seelan et al., 2003). Since that time and with the development of sensors and satellites, agriculture fields have been identified and monitored using remote sensing technics tools. Satellite observations can play a role in providing information about crop type, conditions and yield from field level to extended geographic areas such as countries and continents.

Use of visible and near-infrared portions of electromagnetic spectrum for remote sensing activities have their roots in pioneering work by William Allen, David Gates, Harold Gausman, and Joseph Woolley (Hatfield et al. 2008). These works have led to the understanding of how leaf reflectance changes in response to leaf thickness, species, canopy shape, leaf age, nutrient and water status (Gitelson et al. 2012). Spectral data were studied extensively by using satellite imagery after the launch of the first civil earth observation satellite (Landsat-1) in 1972 (Rembold et al., 2013). Sensors on Landsat 1 revolutionized the remote sensing. They provided imagery in digital format and multi-spectral format. It was the beginning of traditional aerial photographies taken from planes for decades being replaced by digital imagery recorded from satellites. However, have similar analyses been extended to large areas, including many countries in arid and semiarid climates (Johnson et al., 1987; Hutchinson, 1991), only since the growing availability of low spatial resolution satellite images from the meteorological satellite series NOAA (National Oceanic and Atmospheric Administration) AVHRR (Advanced Very High Resolution Radiometer) in the early 80s.

Since then, numerous studies have shown that agricultural production follows strong seasonal patterns related to the biological lifecycle of crops and to climatic conditions. Besides, many researchers suggested that agricultural management practices were so important as physical landscape and climatic variables. All these variables that conduce the yield are highly variable in space and time (Atzberger, 2013). Therefore, understanding distributions and dynamics of agricultural areas is essential to better understand the crops yield and the fundamental plants characteristics and processes, including biogeochemical cycles, crops patterns, phenological phases, and biophysical properties.

Brazil is a country of large territorial extension, where there are crops with several varieties and kinds of management. While there are extensive cultivated areas, there is also familiar agriculture growing in small areas. Moreover, there are many kinds of soil and pluviometric regimes that lead to productivity levels completely different for each region in the country. In this context, several satellites can be used to help the monitoring and estimation of agricultural production.

Until 2000 studies were conducted using satellites available, with medium and low spatial resolution images such as Landsat, SPOT, NOAA and GOES. However, one of the main realized limitations of these satellites was the insufficient spatial resolution. Thus, in past decade, were launched the new generation of satellites: “Very high spatial resolution” such as

IKONOS, QuickBird, WorldView, OrbView-3 and the Panchromatic band of IRS LISS-3, providing the opportunity to study agricultural systems at far greater detail than previously possible. Expectation has been raised about the utility of high spatial resolution satellite imagery for agricultural research.

Nowadays researches have shown that fine spatial resolution provided by these sensors is appropriate to a few analyses but also can lead to problems as the excess of information per pixel (Nagendra et al., 2010) making hard to handle previously simple tasks. Thus, some studies concluded that there appear to be tradeoffs among the utility of different resolutions satellite sensors. Some analyses have a specific demand for spectral, spatial and temporal images resolution, and there is no longer the concept of better or worse images. Different images are used for different purposes and sometimes the combination of characteristics of different images is indicated.

Today, a large range of satellite sensors provide us regularly with data covering a wide spectral range (from optical through microwave). Data are acquired from various orbits and in different spatial and temporal resolutions. The question of choosing the appropriate spatial resolution for a given application has been widely addressed in the remote sensing community (Woodcock et al, 1987, Curran et al, 1988, Townshend et al, 1988, Marceau et al., 1994, Atkinson et al, 1995, Garrigues et al., 2006, McCloy et al, 2007). Some agricultural studies and analyses need accurate, reliable, fine scale and timely estimates of land cover, and in this case, high spatial resolution images are the most indicated (Yang et al. 2011). On the other hand, some analyses need data with high temporal revisit frequency and large spatial coverage. In this case, the most indicated kind of image is high temporal and low spatial resolutions. These images are normally able to detect variation that occurs over time (so called "change detection") and are particularly useful for near real-time information collection at regional scale.

This review aims to provide an overview of recent remote sensing developments in terms of spatial and temporal resolutions applied to monitoring of agricultural fields, especially of sugarcane and coffee crops. To illustrate this issue this paper is structured as follows: in the first part we discuss the importance of low spatial and high temporal resolutions images. In this section, we present studies carried out mainly with sugarcane which has shown good results when analyzing the temporal pattern of crop. In the second part, we discuss the importance of high spatial resolution images, including the new generation of satellites that provides the "ultra-high spatial resolutions images". In this part mainly reference are made to studies with coffee crop fields that has shown good results using images of high spatial resolution. Finally, we attempt to identify the challenges and opportunities of remote sensing for agricultural crops monitoring.

2. LOW SPATIAL AND HIGH TEMPORAL RESOLUTIONS IMAGES

With the improvement of remote sensing technology, large amounts of data have been generated and therefore the analysis and discovery of useful knowledge from these data have become essential tasks to assist research works. However, the potential of satellite multitemporal images to support research of agricultural monitoring has increased according to improvements in technological development, especially in analysis of large volume of data available for knowledge discovery.

Several satellites can be used to aid at monitoring and estimation of agricultural production, especially in a country of large territorial extension as Brazil. Table 1 shows features about a few satellites. One important family of satellites is those belonging to the National Oceanic and Atmospheric Administration (NOAA), such as the Advanced Very High Resolution Radiometer (AVHRR) sensor and the satellite TERRA - Earth Observing System (EOS) with Moderate Resolution Imaging Spectroradiometer (MODIS) sensor.

The AVHRR and MODIS sensors are applied to studies of ecosystems due to the availability of long time series of these data. Moreover, these sensors have global coverage and data with free access which is also other advantage. NOAA-AVHRR images have been used in land-surface studies, such as drought investigation (Bayarjargal et al. 2006, Bajgiran et al. 2008), estimation of crop fields and yield

(Dalezios et al. 2001, Liu and Kogan 2002), and vegetation phenology estimation or evaluation (Maignan et al. 2008). The temporal profile of vegetation index from MODIS expresses different growth cycles for each vegetation type and also phenological differences among years, varying in phase and temporal amplitude. Thus, it is suitable to identify and correctly classify annual crops and pasture land (Rudorff et al. 2009).

Thus, there is a great volume of NOAA/AVHRR multitemporal images that can be used in agriculture to improve monitoring throughout the crop season, in particular agriculture crops that are cultivated in large extensions, such as sugarcane. The production of sugarcane in Brazil, in general, has been growing in last years. Sugarcane crop fields are grow in large and contiguous fields, which allow use of low spatial resolution satellite images (Gonçalves et al. 2011). Channels in the visible and near-infrared spectrum of the AVHRR sensor are used to indicate the amount and state of vegetation through a vegetation index such as the normalized difference vegetation index (NDVI). Time series of NDVI images can contribute to improve the forecasting accuracy of sugarcane crop season.

According to Gonçalves et al. 2012, MVC (Maximum Value Composite) images, having a precise geometric correction, were generated for each month of a 10 year/crop season period (April 2001 to March 2010). Images corresponding to the year/crop season 2003–2004 are shown in Figure 1. The growth evolution of sugarcane can be understood by analyzing MVC images of NDVI in the northeast of São Paulo. The planting usually begins in June (Figure 1(c)) and this aspect is represented by green and blue shades in the NDVI images. These colors represent the low NDVI values, which indicate areas with exposed soil and sparse vegetation. The same color also appears in NDVI images from July to November (Figure 1(d)–(h)). From December (Figure 1(i)), when sugarcane crops present more biomass, these regions in the images acquire yellow, orange and red shades. The maximum NDVI is represented by a stronger red shade when sugarcane crops reach their peak of development from February to May (Figure 1(a, b, k and l)). Dark areas in the images represent pixel coverage by clouds. This phenomenon occurs more mainly in December (Figure 1(i)), January (Figure 1(j)) and February (Figure 1(k)).

In this context, a methodology based on data clustering to analyze NDVI multitemporal images, in order to monitor the expansion of sugarcane crops, show that this approach can identify regions of sugarcane fields and areas with spectral mixture or noise (Romani et al. 2011). The whole process, including extraction of NDVI profiles, clustering methods and geospatial visualization, was implemented in a new system named SatImagExplorer (Chino et al. 2010). Figure 2 shows the resulting MVC images and clusters generated by the clustering method (K-Means) on the region of São Paulo, where Cluster 1 (blue) indicates medium-low NDVI, and Cluster 2 (red) indicates high NDVI. From December to May, Cluster 2 is predominant, corresponding to high NDVI values. However, from June to November, when NDVI is low (green tones in images MVC), Cluster 1 is predominant. Therefore, the grouping of NDVI values coincides to the evolution of vegetative growth of sugarcane.

Another application of remote sensing and data mining is clustering analysis using K-Medoids and the distance function DTW (Dynamic Time Warping) were made in five clusters with NDVI profile using AVHRR/NOAA and MODIS (Gonçalves et al. 2013). Finally, the statistical analysis (Pearson correlation) done with clusters of the planted and harvested area and crop yield. The clusters identified pixels related to the sugarcane planting areas and spectral mixture.

Results obtained from MODIS images reached R values greater than for AVHRR/NOAA, because that sensor has a spatial resolution of 250m, with more details from sugarcane fields. However, AVHRR/NOAA also obtained satisfactory results. All these studies show that it is possible to use data from low spatial resolution sensors to monitor crop fields planted over large areas. The advantage of these sensor systems is their high temporal resolution, low cost and global coverage.

3. HIGH SPATIAL AND LOW TEMPORAL RESOLUTIONS IMAGES

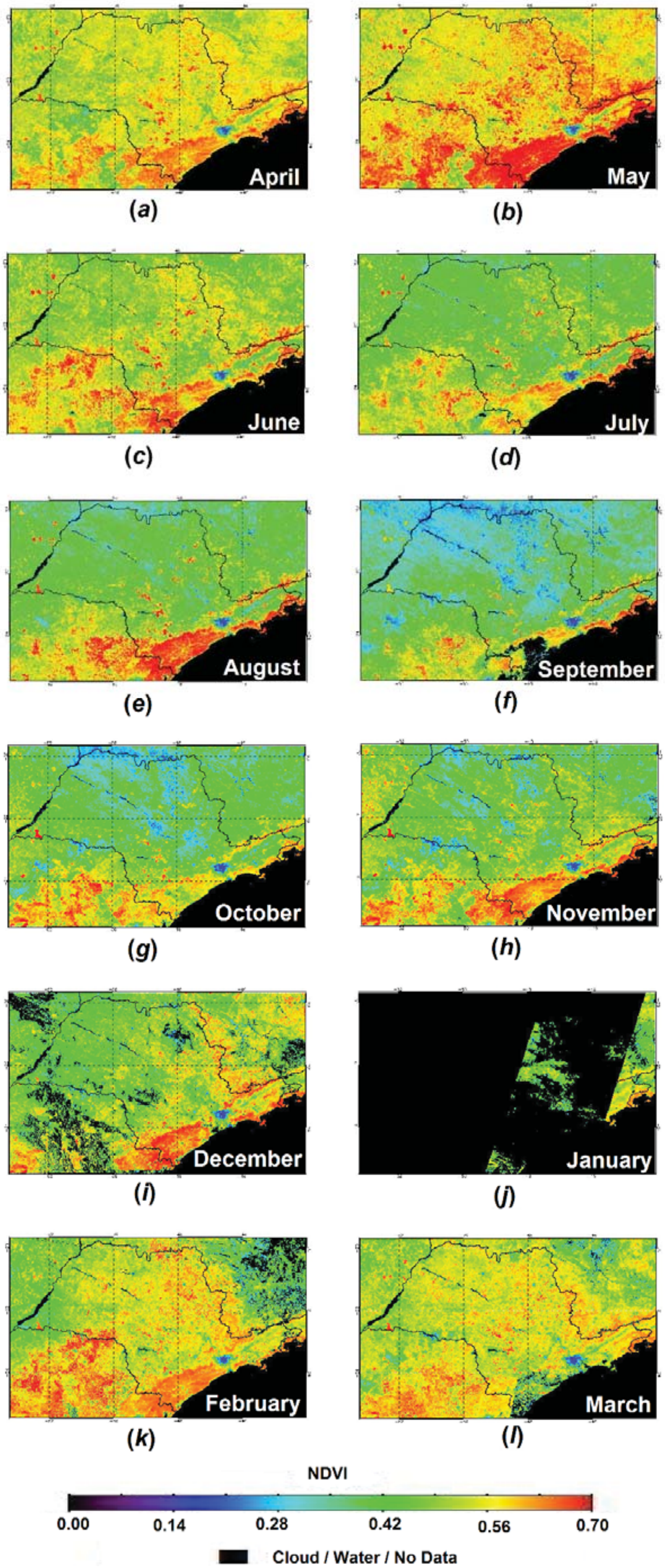

Fig. 1 - Images of 2003-2004 year/crop season, where sugarcane biomass varies from high NDVI values in red (February–May) to low NDVI values in green and blue shades (July–September).

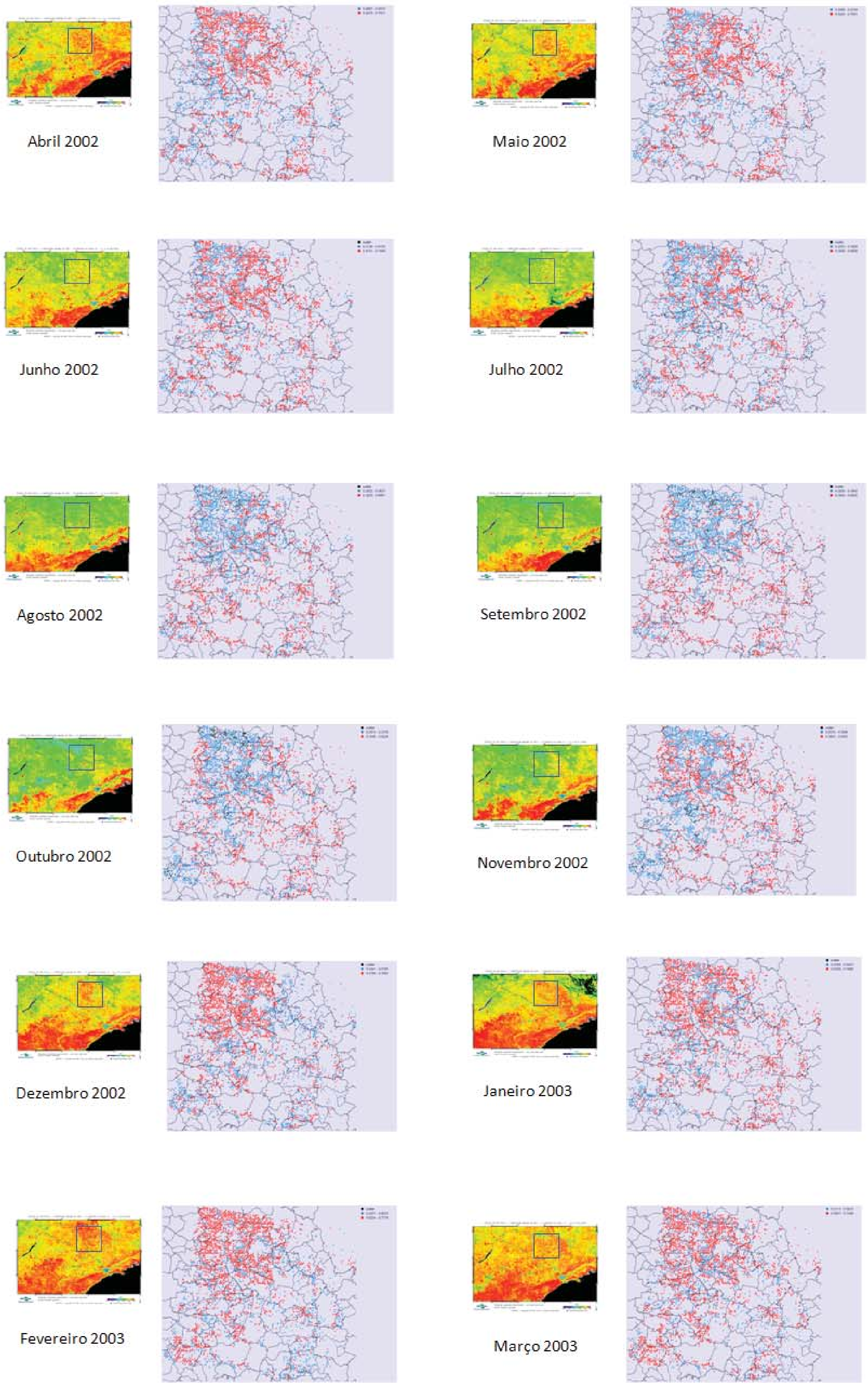

Fig. 2 - MVC images of NDVI and clusters of NDVI (2 clusters) from São Paulo from April 2002 to March 2003.

Table 1: Low Spatial Resolution Satellites

Sensor/Satellite	Spatial Resolution (meters)	Temporal Resolution	Number of Spectral Bands	Launched
AVHRR/NOAA	1100	12 hours	6 bands	October, 1978
GOES	1000, 4000 or 8000	30 minutes	28 bands	October, 1975
MODIS/TERRA	250, 500 or 1000	1 - 2 days	36 bands	December, 1999
SPOT VEGETATION	1165	1 day	4 bands	March, 1998

In worldwide, use of current high spatial resolution imagery in vegetation studies is increasing due to their improved efficiency, as fine-scale vegetation data. This information is needed for both theoretical understanding of the processes involved and conservation towards the maintenance of ecological functions of natural ecosystems (Gairola et al., 2013).

Sensors with high spatial and low temporal resolutions, usually present less than 30 meter pixel spatial resolution, and the time to recover the same place ranges from daily to 26 days (Table 2). High spatial resolution images can be divided in two main groups: (i) high resolution missions as Landsat, SPOT, ASTER and CBERS, sometimes also called “medium resolution” and (ii) the new generation of high spatial resolution images, also called “ultra-high” or “very high” resolution images, such as IKONOS, QuickBird, SPOT-5, Geoeye-1, RapidEye, WorldView-1 and WorldView-2. The most useful sensors for agricultural studies are presented in Table 2.

Although the two groups are considered high spatial resolution images, there are differences in data application, and data choice depends on the goal and details of analyses. Each group has advantages and disadvantages. The possibility of using high spatial resolution images depends on many factors: sensors features (geometric and radiometric resolution), types of products available, cost and time to obtain the products, cost of commercial software for processing these images. The main difference between the two groups is the detail and amount of the information, which is bigger in the “ultra-high spatial resolution images” group.

The spatial resolution for the first group ranges from 15 meters (for ASTER VNIR) to 30 meters (for Landsat TM), and the temporal resolution ranges from 16 days (Landsat TM and ASTER) to 26 days (CBERS and SPOT). However, this group has the main advantage of having a very low cost, being normally free with easy access, which enables the utilization, including the usage of time series images, as was done by Pereira-Coltri et al. (2011), who were able to analyze the growth of coffee biomass using Landsat TM time series images from 2004 to 2010. North et al. (2012) also used 5-7 years of temporal signature from Landsat and SPOT to classify complex agricultural land use patterns in New Zealand.

High spatial resolution has long been used to monitor crop growing conditions (Pereira-Coltri et al., 2011), to estimate crop yields (Almeida et al., 2006), identify agricultural fields (Andrade et al., 2013; North et al., 2012; Barbosa et al; 2010; Ramirez et al., 2006) estimate crop parameters (Ramirez et al., 2010; Ramirez et al., 2011; Pereira-Coltri et al., 2011), identify land cover and land use (Kolios et al., 2013), monitor evapotranspiration (Anderson et al., 2012), and estimate climate change relevant emissions (Collins et al., 2008). In addition, these high spatial resolution images also allow monitor crop health status (Bing et al., 2012) and detect disease incidence (Chen et al., 2007).

These images can be used in a big range of important crops (e.g. coffee, sugarcane, bean, soybean, maize and others) and also can be used for studies of forest systems. In terms of high spatial resolution images, Landsat is the most widely used satellite, especially for the global coverage and accessibility of images. A common approach in these studies for measuring or monitoring crop growth is the correlation between vegetation indices (or ratios) and crop variables, as percentage of vegetation coverage, biomass and leaf area index (LAI) (Ramirez et al., 2011; Pereira-Coltri et al., 2011). Several studies using Landsat TM has been done to monitor important agricultural crops in Brazil as sugarcane (Rudorff et al., 2010) soybean (Mercante et al., 2009), rice (McCloy et al., 1987) and others. Coffee, as an important crop and global commodity, also has been monitored (Ramirez et al., 2010; Ramirez et al., 2011; Pereira-Coltri et al., 2011) and identified (Andrade et al., 2013; Barbosa et al; 2010; Moreira et al. 2004) using Landsat images. Ramirez et al (2011) assess LANDSAT-TM to estimate important coffee biophysical parameters in São Paulo (Brazil) and concluded that coffee leaf area index (LAI) can be related with blue and green bands. In addition, coffee plant height also had good relationship with blue band. Pereira-Coltri et al. (2011) also used Landsat-TM to assess coffee biomass and carbon stock, suggesting that coffee crop can mitigate the greenhouses gases (GEE), in a climate change approach. Authors also concluded that it is possible to monitor coffee biomass and carbon stock using vegetation index as NDVI and SAVI from Landsat images. In that work, authors showed that Landsat vegetation index can also monitor season rain variation. One month after a large period of drought the vegetation index decrease.

The second group of high spatial resolution satellites, the "very-high spatial resolution images", became available more recently, and both spatial and temporal resolutions are better than first group, enabling scientists to study vegetation systems in more detailed scale (Gariola et al., 2013). Normally, the resolution of this new generation of images is less than 5 meters (Aguilar et al., 2013). For example, in the multispectral resolution data at nadir, very high spatial resolution images normally ranges from 1.65 meters (for Geoeye-1) to 5 meters (for RapidEye) and, temporal resolution ranges from daily to 5.5 days (for RapidEye). In this context, very high spatial resolution images are more detailed in space and time. Figure 3 shows an example of a coffee area in Geoeye-1 image (Pereira-Coltri et al., 2013).

These images, such as IKONOS and GeoEye-1, combine high spatial resolution with a broad area coverage (Dufour et al., 2012), providing to a new type of detailed information such as plant stand structure, individual tree crowns (Hurtt et al. 2003; Levin et al. 2007; Rocchini 2007; Pereira-Coltri et al., 2013), canopy diameters (Pereira-Coltri et al., 2013), age-class distribution (Singh et al. 2010) and structural information on dominance (Singh et al. 2010). In this context, these images became important for many types of studies, and could be a suitable alternative to aerial photogrammetric data to update and produce maps at 1:5000 scale or better (Gariola et al., 2013).

Usually, very high resolution systems have the disadvantages of being much more expensive than the first group. Moreover the time to get the images is bigger, which sometimes can difficult the time series utilization, and in this context, the advantage of higher temporal resolution can be lost. Most studies that use very high resolution images do not use time series.

Several researches have shown that very high spatial resolution images can be used for a number of applications such as crop inventory and identification (Yang et al. 2011; Pereira-Coltri et al., 2011b; Ramirez et al., 2006), biodiversity studies in forests (Gairola et al., 2013), crop conditions and parameters (Ramirez et al., 2006; Pereira-Coltri et al., 2013); crop production forecasts, fruit quality, leaf area index analyses (Pereira-Coltri et al., 2013), biomass estimation (Pereira-Coltri et al., 2013), carbon stock and sequestration (Pereira-Coltri et al., 2013); horticultural studies (Ucha and Singh, 2013) drought and flood damage assessment, range and irrigated land monitoring and management (Min et al., 2008; Mondal and Basu, 2009). From a practical point of view, this kind of images is used on a very fine scale, when analyses need accurate data, data points or when the crop fields are small. For example, Pereira-Coltri et al. (2013) explain that especially for coffee fields, the new very high resolution satellites support overcoming a classical monitoring challenge, which is the scale. About 70% of the world coffee fields is grown on small holdings smaller than 10 ha, often as a family business. By capturing the small production areas, very high spatial resolution satellites are important to monitor biophysical properties. In that article, authors estimate biomass and propose an empirical relationship to predict coffee biomass and carbon stock using Geoeye-1. That study is in agreement with Ramirez et al. (2006), which assess the impact of the better resolution to identify coffee fields. Authors concluded that IKONOS identify more coffee fields than Landsat TM.

Although very high spatial resolution images offer the very accurate data, sometimes this data is too much fine to analyses and the cost-benefit relation becomes improper. Nagendra et al. (2010) compare IKONOS and Landsat satellite to evaluate plant diversity in a dry tropical forest, in central India. Across multiple measures of plant distribution and diversity, authors concluded that resolution of the IKONOS data is too fine for the purpose of plant diversity assessment and Landsat imagery performs better.

In this case, authors explain that when spatial resolution is so high that pixels are at least an order of magnitude smaller than that of the object being categorized, the variability of the information provided by pixels covering a single correspondingly increases, to the point that accurate identification can became very difficult.

In conclusion, high spatial resolution images can be used in a range of agricultural studies, and the choice of each resolution will depend on the need for detailed scale, the spectral range, the temporal resolution and on the cost-benefit relationship. Usually, if the analyses need very fine scale, very high spatial resolution images are more indicated. However, if the analyses do not need too much detail, low spatial resolution images are indicated, mainly for the easy access and the low cost.

4. CONCLUSION AND OUTLOOK

The review demonstrates the strong role that remote sensing plays within the agricultural sector using high, medium or low spatial resolution images. As discussed there are no better or worse images, but different images and different goals and analyses.

After the launch of IKONOS satellite, very high spatial resolution satellite images have become increasingly popular, making detailed images of large parts of the Earth easily available to a larger public. At this time, many studies were done to verify the efficiency of very high spatial resolution images, and the difference between these images and Landsat/TM, for example. Most studies concluded that when there is a need to analyze fine scale and we need detailed information at the tree level (as plant stand, canopy diameter, and biomass per tree), very high spatial resolution images are indicated. Some agriculture fields, as coffee, always had a classical monitoring challenge, which is the scale, and in this case, good results have also been obtained using very high spatial resolution images. For example, studies to estimate coffee biophysical properties using very high spatial resolution images presented high correlation (normally more than 0.6) with field measurements. It is also emphasize to comment that to choose the better option it is important to analyze the cost-benefit relationship. Sometimes, medium spatial resolution images can have a better performance than very high spatial resolution images. In addition, some studies also pointed out that Landsat/TM data, which are more readily available over all parts of Earth, are normally available free to the global research community.

Sometimes the agricultural analysis need regional scale and temporal revisit frequency, and in this case low spatial resolution satellite images for crop monitoring and yield prediction is more indicated. The large number of existing studies proves the relevance of low spatial resolution satellite at regional level and under different environmental circumstances. The relatively limited costs generally associated with the acquisition of low spatial resolution satellite images makes them an attractive instrument for crop monitoring and yield forecasting.

The high spatial temporal resolution enables to monitor and estimate harvests of crops planted over large fields, as sugarcane. This kind of monitoring is especially important to Brazil which is the largest sugarcane producer in the world, contributing with 35% of the global production. The described method of analyze NDVI clustering information allows monitor the planting and the harvest of sugarcane in a large and important area, as São Paulo state, for example.

More recently a new approach has combined indicating that, often, the best solution is the use of data from different sensors with different characteristics. In this case, there would be the possibility of working with fine spatial resolution and high temporal resolution, but,

Table 2: High Spatial Resolution Satellites

Satellite	Spatial Resolution (meters)	Temporal Resolution	Number of Spectral Bands	Launched
(i) First Group - High Spatial Resolution Images				
Landsat -5 (TM)	30	16 days	7 bands	March, 1984
SPOT	10 and 20	26 days	5 bands	1st launched in February, 1986
ASTER - VNIR	15	16 days	3 bands	December, 1999
CBERS -2	20	26 days	5 bands	October, 2003
(ii) Second Group- Ultra-high resolution images				
IKONOS	Pan: 0.82 MS: 3.2	3 days	5 bands	September, 1999
QuickBird	Pan: 0.61 MS: 2.44	1 – 3.5 days	5 bands	October, 2001
Geoeye-1	Pan: 0.41 MS: 1.65	3 days	5 bands	September, 2008
RapidEye	MS: 5.0	Daily (nadir) to 5.5 days	5 bands	August, 2008
WorldView-1	Pan: 0.5 MS: na	1.7 to 5.9 days	1 band - panchromatic	September, 2007
WorldView-2	MS: 1.8 – 2.4	1.1 – 3.7 days	8 multispectral bands	October, 2009
OrbView-3	Pan: 1.0 MS: 4.0	3 days	5 bands	June, 2003

Pan: panchromatic; MS: Multispectral

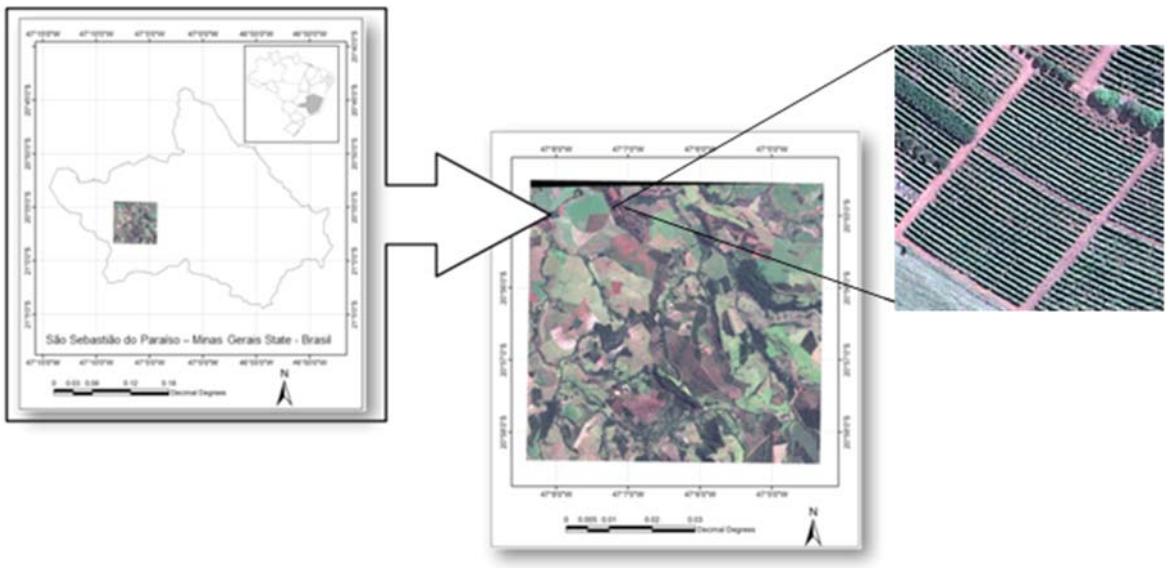

Fig 3 - Example of Coffee Area in South of Minas Gerais, Brazil, using Geoeye-1 image (RGB composition) (Pereira-Coltri et al., 2013).

once again, it depends on the purpose of the analysis to be done.

It is important to note that all remote sensing tools generate a huge volume of data. In last decade, improvements in data collection methods and sensor technology, as well as the large number of new remote sensing satellite launchings have fostered an increase in the capabilities of acquiring spatial data. As a consequence, the volume of satellite images stored in institutions in the world exceeds the human analysis capability, and the only way that can be expect to understanding the potential information it embodies counting on the support of automated data analysis tools. In this context, the use of data mining, big data and systems designated for clustering methods and geospatial visualization (as described with

SatImagExplorer) is necessary. It is important to work with technological advances in gathering and processing a large volume of satellite images assists the analysis of remote sensing data, in order to better visualize the agricultural fields development.

REFERENCES

AGUILAR M. A. *et al*., “Assessing geometric accuracy of the orthorectification process from GeoEye-1 and WorldView-2 panchromatic images,” **Int. J. Appl. Earth Observ. Geoinf**., vol. 21, p. 427–435, 2013.

ALMEIDA, T.I.R.; SOUZA FILHO, C.R.; ROSSETO, R. Aster and Landsat ETM+ images applied to sugarcane yield forecast. **International Journal of Remote Sensing**, vol. 27, n 19, 2006.

ANDERSON, M.C.; ALLEN, R.G., MORSE, A.; KUSTAS, W.P. Use of landsat thermal imagery in monitoring evapotranspiration and managing water resources. **Remote Sensing of environment**, v.122, p.50-65, july 2012.

ANDRADE, L.N.D.; VIEIRA, T.G.C. ; LACERDA, W.S. ; VOLPATO, M.M.L. ; DAVIS JUNIOR, C. ; Aplicação de redes neurais artificiais na classificação de áreas cafeeiras em Machado-MG. **Coffee Science**, v.8, p.78-90, 2013.

ATZBERGER, C. Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. **Remote Sensing,** *vol. 5, n. 8,* 2013.

ATKINSON, P.M.; CURRAN, P.J. Defining an optimal size of support for remote-sensing investigations, **IEEE Transactions on Geoscience and Remote Sensing, vol.** 33, n.3, p. 768–776, 1995.

BAJGIRAN, P. R., DARVISHSEFAT, A. A., KHALILI, A., MAKHDOUM, M. F.Using AVHRR-based vegetation indices for drought monitoring in the Northwest of Iran. **Journal of Arid Environments**, 72, p. 1086–1096. 2008

BAYARJARGAL, Y., KARNIELI, A., AYASGALAN, M., KHUDULMUR, S., GANDUSH, C. TUCKER, C. A comparative study of NOAA-AVHRR derived drought indices using change vector analysis. **Remote Sensing of Environment**, vol.105, p. 9–22, 2006

BARBOSA, J.N.; BOREM, F.M.; ALVES, H.M.R.; VOLPATO, M.M.L.; VIEIRA, T.G.C.; SOUZA, V.C.O. Spatial distribution of coffe from Minas Gerais State and their relation with quality. **Coffee Scince**, v.5; p.237-250, 2010.

CHEN, X.; MA, J.; QIAO, H.; CHENG, D.; XU, Y. ; ZHAO, Y. Detecting infestation of take-all disease in wheat using Landsat Thematic Mapper imagery. **International Journal of Remote Sensing**, v.28, n.22, 2007.

CHINO, D. Y. T., ROMANI, L. A. S., TRAINA, A. J. M. Construindo séries temporais de imagens de satélite para sumarização de dados climáticos e monitoramento de safras agrícolas. **Revista Eletrônica de Iniciação Científica**, vol. 10, p. 1–16, 2010.

CURRAN, P.J.; WILLIAMSON. H.D. Selecting a spatial-resolution for estimation of per-field green leaf-area index, **International Journal of Remote Sensing**, vol. 9, n.7, p. 1243–1250, 1988.

DALEZIOS, N.R., DOMENIKIOTIS, C., LOUKAS, A., TZORTZIOS, S.T., KALAITZIDIS, C. Cotton yield estimation based on NOAA/AVHRR produced NDVI. Physics and Chemistry of the Earth, Part B: **Hydrology, Oceans and Atmosphere**, vol. 26, p. 247–251, 2001.

DUFOUR, S.; MULLER, E.; STRAATSMA, M. and CORGNE, S. Image utilization for the Study and Management of Riparian Vegetation: Overview and Applications. In **Book Fluvial Remote Sensing for Scince Management**. Cap 10. , 2012. 215p.

GAIROLA, S.; PROCHE, S., ROCCHINI, D. High-resolution satellite remote sensing: a new frontier for biodiversity exploration in Indian Himalayan forests. **International Journal of Remote Sensing**, vol. 34, n. 6, p.2006–2022, Mar. 2013,

GARRIGUES, S.; ALLARD, D.; BARET, F.; WEISS, M. Quantifying spatial heterogeneity at the landscape scale using variogram models. **Remote Sensing of Environment**, vol.103, n.1, p. 81–96, 2006.

GITELSON, A.A. *et al*. Remote estimation of crop gross primary production with Landsat data. **Remote Sensing of Environment**, vol. 121, p. 404–414, 2012.

GONÇALVES, R. R. V., ZULLO JUNIOR, J., FERRARESSO, C. S., SOUSA, E. P. M., ROMANI, L. A. S., and TRAINA, A. J. M. Analysis of NOAA/AVHRR multitemporal images, climate conditions and cultivated land of sugarcane fields applied to agricultural monitoring. In: Sixth International Workshop on the Analysis of Multi-temporal Remote Sensing Images (MultiTemp-2011). **Anais**. vol. VI, p.229-232, Trento, Italia, 2011.

GONÇALVES, R. R. V.; ZULLO JUNIOR, J.; ROMANI, L. A. S.; NASCIMENTO, C. R.; TRAINA, A. J. M. Analysis of NDVI time series using cross-correlation and forecasting methods for monitoring sugarcane fields in Brazil". **International Journal of Remote Sensing**, 33:15, pp. 4653-4672, 2012.

GONÇALVES, R. R. V.; ZULLO JUNIOR, J.; MARQUEZINI, O.; AMARAL, B. F.; SOUSA, E. P. M.; ROMANI, L. A. S. Análise da relação entre os perfis de NDVI obtidos dos sensores AVHRR/NOAA e MODIS nas áreas produtoras de cana-de-açúcar em São Paulo. In: XVI Simpósio Brasileiro de Sensoriamento Remoto - SBSR, 2013, Foz do Iguaçu, PR. **Anais** XVI Simpósio Brasileiro de Sensoriamento Remoto - SBSR, 2013. p. 640-647.

HATFIELD, J.L.; GITELSON, A.A.; SCHEPERS, J.S.; WALTHALL, C.L. Application of Spectral Remote Sensing for Agronomic Decisions. **Agronomy Journal**, vol. 100, n.3, p. 117-131, 2008.

HURTT, G., XIAO, X.; KELLER, M.; PALACE, M. ASNER, G. P.; BRASWELL, R. IKONOS Imagery for the Large Scale Biosphere-Atmosphere Experiment in Amazonia (LBA). **Remote Sensing of Environment** vol. 88, n.111, p.27, 2003.

HUTCHINSON, C.F. Uses of satellite data for famine early warning in Sub-Saharan Africa. **Int. J.Remote Sens**., vol.12, p.1405–1421, 1991.

JOHNSON, G.E.; VAN DIJK, A.; SAKAMOTO, C.M. The use of AVHRR data in operational agricultural assessment in Africa. **Geocarto Int**., vol. 2, p.41–60, 1987.

KOLIOS, S.; STYLIOS, C.D. Identification of Land cover/land use changes in the greater area of the Preveza peninsula in Greece using Landsat satellite data**. Applied Geography**, vol. 40, p.150-160, jun. 2013.

LEVIN, N., SHMIDA, A.; LEVANONI, O.; TAMARI, H.; KARK, S. Predicting Mountain Plant Richness and Rarity from Space Using Satellite-Derived Vegetation Indices. **Diversity and Distributions**, vol. 13, p. 692–703. 2007.

LIU, W.T., KOGAN, F. Monitoring Brazilian soybean production using NOAA/AVHRR based vegetation condition indices. **International Journal of Remote Sensing**, vol. 23, p. 1161–1179, 2002.

MAIGNAN, F., BRÉON, F.M., BACOUR, C., DEMARTY, J.; POIRSON, A. Interannual vegetation phenology estimates from global AVHRR measurements Comparison with in situ data and applications. **Remote Sensing of Environment**, vol. 112, p. 496–505, 2008.

MARCEAU, D.J.; GRATTON, D.J.; FOURNIER, R.A. FORTIN. J.-P. Remote sensing and the measurement of geographical entities in a forested environment. The optimal spatial resolution. **Remote Sensing of Environment**, vol. 49, n.2, p. 105–117, 1994.

MCCLOY, K.R.; SMITH, F.R.; ROBINSON, M.R. Monitoring rice using LANDSAT MSS data. **International Journal of remote sensing**, v.8, n 5, 741-749. 1987.

MCCLOY, K.R.; BOCHER, P.K. Optimizing image resolution to maximize the accuracy of hard classification. **Photogrammetric Engineering and Remote Sensing**, vol.73, n. 8, p. 893–903, 2007.

MERCANTE, E.; LAMPARELLI, R. A. C.; URIBE-OPAZO, M. A.; ROCHA, J. V. Características espectrais da soja ao longo do ciclo vegetativo com imagens landsat 5/TM em área agrícola no oeste do Paraná. **Engenharia Agrícola**, v.29, n.2, p. 328-338, 2009.

MOREIRA, M.A; ADAMI, M.; RURDOFF, B.F.T. Análise espectral e temporal da cultura do café em imagens landsat. **Pesquisa Agropecuaria Brasileira**, v. 39, n.3, p.223-231. 2004.

NAGENDRA, H.; ROCCHINI, D.; GHATE, R.; SHARMA, B. ; PAREETH, S. Assesing plant diversity in a dry tropical forest : comparing the utility of Landsat and Ikonos Satellite images**.** **Remote Sensing**, v.2, n.2, pp.478-496, 2010.

NORTH, H.; PAIRMAN, D.; BELISS, S.E.; CUFF, J. Classifying agricultural land uses with time series of satellite images. In.: Geoscience and Remote Sensing Symposium (IGARSS), 2012, IEEE International. **Anais.** p. 5693-5696, Munich, 2012.

PEREIRA COLTRI, P.; ROMANI, L.A.S.; DUBREUIL, V.; CORGNE, S.; ZULLO JUNIOR, J.; PINTO, H.S. Variação temporal da biomass do café arábica arborizado e a pleno sol, através de índices de vegetação. In: Anais do XV Simposio Brasileiro de Sensoriamento Remoto, **Anais**. P. 531-538, Curitiba. 2011.

PEREIRA-COLTRI, P.; CORDEIRO, R.L.F.; SOUZA, T.T.; ROMANI, L.A.S.; ZULLO JUNIOR, J.; TRAINA JUNIOR, C.; TRAINA, A.J.M. Classificação em áreas de café em Minas Gerais por meio do novo algoritimo QMAS em imagem espectral Geoeye-1. In: Anais do XV Simposio Brasileiro de Sensoriamento Remoto, **Anais**. Curitiba. P. 539-546, 2011b.

PEREIRA COLTRI, P**.** ; ZULLO JUNIOR, J. ; GONCALVES, R. R.V.; ROMANI, L. A.; PINTO, H.S. Coffee Crop's Biomass and Carbon Stock Estimation With Usage of High Resolution Satellites Images. **IEEE J-STARS**, v. 6, n.3.,p. 1786-1795, 2013.

RAMIREZ, G. M.; ZULLO JUNIOR, J. Estimativa de parâmetros biofísicos de plantios de café a partir de imagens orbitais de alta resolução espacial. **Eng. Agríc.**, v. 30, n. 3, p. 468-479, Jun. 2010.

RAMIREZ, G. M.; ZULLO JUNIOR, J. Utilização de imagem do satélite Landsat/TM na determinação de parâmetros biofísicos de plantios de café. In: Anais do XV Simposio Brasileiro de Sensoriamento Remoto, Curitiba, **Anais**. p.247-253. 2011.

REMBOLD, F.; ATZBERGER, C.; SAVIN, I.; ROJAS, O. Using Low Resolution Satellite Imagery for Yield Prediction and Yield Anomaly Detection. **Remote Sens**., vol.5, p. 1704-173, 2013.

ROCCHINI, D. Effects of Spatial and Spectral Resolution in Estimating Ecosystem α-Diversity by Satellite Imagery. **Remote Sensing of Environment**, vol.111, p.423–34, 2007.

ROMANI, L. A. S., GONÇALVES, R. R. V., AMARAL, B. F., CHINO, D. Y. T., ZULLO JUNIOR, J., TRAINA JUNIOR, C., SOUSA, E. P. M., TRAINA, A. J. M. Clustering analysis applied to NDVI/NOAA multitemporal images to improve the monitoring process of sugarcane crops. In: Sixth International Workshop on the Analysis of Multi-temporal Remote Sensing Images (MultiTemp-2011). **Anais**. Trento, Italia, vol. VI, pp.33-36, 2011.

RUDORFF, B. F. T., ADAMI, M., AGUIAR, D. A., GUSSO, A., SILVA, W. F., FREITAS, R. M. Temporal series of EVI/MODIS to identify land converted to sugarcane. In: IEEE International Geoscience and Remote Sensing Symposium - IGARSS 2009. **Anais**. Cape Town, South Africa, vol. IV, pp. 252–255, 2009.

RUDORFF, B.F.T.; AGUIAR, D.A.; SILVA, W.F.; SUGAWARA, L.M.; ADAMI, M.; MOREIRA, M.A. Studies on the rapid expqnsion of sugarcane for etanol production in São Paulo state (Brazil) using Landsat data. **Remote Sensing**, vol.2, n.4, 1057-1076. 2010.

SEELAN, S.K, SOIZIK L.; CASADY, G.M.; SEIELSTAD, G.A. Remote sensing applications for precision agriculture: A learning community approach. **Remote Sensing of Environment**, vol. 88, n. 1–2, p. 157–169, 2003.

TOWNSHEND, J.R.G.; JUSTICE, C.O. Selecting the spatial resolution of satellite sensors required for global monitoring of land transformations, **International Journal of Remote Sensing**, vol.9, n.2, p. 187–236, 1988.

WOODCOCK, C.E.; STRAHLER, A.H. The factor of scale in remote sensing, **Remote Sensing of Environment**, vol. 21, issue 3, pp. 311–332, 1987.

YANG, S. *et al.* Remote Sensing Applications in Qinghai Yushu Earthquake Monitoring and Assessment. **Spacecraft Engineering**, vol.20, n.6, p. 90-96, 2011.