University of São Paulo
“Luiz de Queiroz” College of Agriculture

**Three-dimensional modeling of radiative transfer and canopy
reflectance in *Eucalyptus* stands**

Julianne de Castro Oliveira

Thesis presented to obtain the degree of Doctor in
Science. Area: Forest Resources. Sub-area: Silviculture
and Forest Management

Piracicaba
2016

Julianne de Castro Oliveira
Forest Engineer

**Three-dimensional radiative transfer modeling of radiative transfer and canopy
reflectance in *Eucalyptus* stands**

versão revisada de acordo com a resolução CoPGr 6018 de 2011

Advisor:
Prof. Dr. **LUIZ CARLOS ESTRIVIZ RODRIGUEZ**

Thesis presented to obtain the degree of Doctor in
Science. Area: Forest Resources. Sub-area: Silviculture
and Forest Management

Piracicaba
2016

**Dados Internacionais de Catalogação na Publicação
DIVISÃO DE BIBLIOTECA - DIBD/ESALQ/USP**

Oliveira, Julianne de Castro

Three-dimensional modeling of radiative transfer and canopy reflectance in *Eucalyptus* stands / Julianne de Castro Oliveira. - - versão revisada de acordo com a resolução CoPGr 6018 de 2011. - - Piracicaba, 2016.
120 p. : il.

Tese (Doutorado) - - Escola Superior de Agricultura "Luiz de Queiroz".

1. DART 2. Reflectância 3. Imagem de satélite 4. Plantações florestais I. Título

CDD 634.9734
O49t

"Permitida a cópia total ou parcial deste documento, desde que citada a fonte – O autor"

ACKNOWLEDGMENTS

I would like to thank my advisor Professor Ph.D. Luiz Carlos Estraviz Rodriguez for the guidance, teachings and the technical and emotional support.

I am grateful to researcher Ph.D. Gueric le Maire for the partnership, professional support and availability.

I am grateful to Professor Ph.D. José Alexandre M. Demattê and researchers Ph.D. Flávio Ponzoni and Ph.D. Yann Nouvellon for the attention and support during this graduate course and for the suggestions in this work.

I would like to thank researchers Ph.D. Jean-Philippe Gastellu-Etchegorry, Ph.D. Jean-Baptiste Féret and Ph.D. Eloi Grau for the technical support with DART and simulations.

I am grateful to the Eucflux Project and all partners, enterprises, and engaged staff for providing the data and supports to develop this work.

I would like to thank researchers and staff members of UMR Eco&Sols for the reception, support and grateful moments during my sandwich period in France.

I would like to express my gratitude to the Forest Resources Graduate Program - ESALQ/USP for the opportunity to attend the Ph.D. and all staff members, particularly, Jefferson L. Polizel and Giovana Oliveira, for the technical and emotional support.

I would like to thank CAPES - PDSE Program for granting me a scholarship to conduct my doctoral sandwich abroad.

I am thankful for the doctoral scholarship provided by CNPq.

I would like to thank my family and my boyfriend to be a source of encouragement and inspiration to me throughout my life.

I am grateful to my Brazilian and French friends and my dog for supporting me spiritually and providing me very good moments during this entire graduate program.

I would like to thank my roommate and lab partners of the Get-LiDAR research group for sharing very helpful debates, skills and good moments.

EPIGRAFY

"Everything is theoretically impossible, until it is done"

Robert A. Heinlein

SUMMARY

RESUMO	9
ABSTRACT	11
1 INTRODUCTION	13
1.1 Brazilian eucalyptus plantations	15
1.2 Forest biophysical parameters	16
1.3 Leaf Area Index(LAI).....	16
1.4 Leaf Angle Distribution(LAD).....	18
1.5 Fraction of Absorbed Photosynthetically Active Radiation (fAPAR)	20
1.6 Remote sensing of forest stands	21
1.7 Spectral Vegetation Indices(SVI's)	26
1.8 Radiative transfer models of vegetation	28
1.9 DART model	30
1.10 Objectives of the thesis.....	33
1.11 Thesis structure.....	33
References	34
2 ACCURACY OF DART MODEL TO SIMULATE VERY HIGH RESOLUTION IMAGES AT DIFFERENT AGES AND CLONAL MATERIALS OF EUCALYPTUS STANDS.....	47
Abstract.....	47
2.1 Introduction	48
2.2 Material and Methods.....	49
2.2.1 Study Area	49
2.2.2 In situ measurements	52
2.2.3 The 3D DART radiative transfer model	55
2.2.4 DART parameterization	55
2.2.4.1 Spectral intervals	55
2.2.4.2 Illumination parameters.....	56
2.2.4.3 Scene.....	56
2.2.4.4 Tree parameters	57
2.2.4.4.1 Trees dimensions	57
2.2.4.4.2 Leaf Angle Distribution (LAD).....	57
2.2.4.4.3 Leaf Area Index (LAI).....	58

2.2.4.4.4 Leaves, trunk and soil optical properties	59
2.2.5 Atmospheric Correction.....	59
2.2.6 WorldView-2 Satellite images	60
2.2.7 Realism of simulated scenes in DART	61
2.2.8 Comparison between simulated and satellite images.....	61
2.3 Results and Discussion.....	62
2.3.1 Optical properties and Chlorophyll content	62
2.3.2 Atmospheric correction.....	69
2.3.3 Structural analysis of simulated trees.....	70
2.3.4 Analysis of DART simulated images.....	74
2.4 Conclusions.....	83
References.....	84
3 RELATIONSHIP BETWEEN LEAF AREA INDEX AND SPECTRAL VEGETATION INDICES IN EUCALYPTUS STANDS USING VERY HIGH SPATIAL RESOLUTION SIMULATED IMAGES FROM DART MODEL.....	89
Abstract	89
3.1 Introduction.....	90
3.2 Material and Methods	92
3.2.1 Study Area.....	92
3.2.2 In-situ measurements of LAI and other stand biophysical properties	93
3.2.3 Worldview 2 images and creation of the experimental dataset	95
3.2.4 The 3D DART radiative transfer model	96
3.2.5 Creation of a reflectance simulation dataset.....	96
3.2.6 Spectral vegetation indices and regressions with LAI.....	97
3.2.7 Statistical analysis	99
3.3 Results.....	101
3.3.1 LAI - SVI calibrations on experimental dataset.....	101
3.3.2 LAI - SVI calibrations on simulation dataset.....	103
3.3.3 Comparison of the experimental and simulation results	107
3.3.4 Application of the vegetation indices to satellite images.....	109
3.4 Discussion	111
3.5 Conclusions.....	114
References.....	114
4 GENERAL CONCLUSION	1179

RESUMO

Modelagem tridimensional da transferência de radiação e reflectância de dosséis de povoamentos de Eucalipto

Modelos de transferência de radiação (MTR) têm sido utilizados com sucesso para simular o efeito das características estruturais e bioquímicas florestais, como tamanhos de árvores e formas, índice de área foliar (IAF), distribuição angular das folhas (DAF) e sobre o balanço de radiação. Um uso particular do MTR é a análise da radiação refletida pela copa, o que pode ser medido através de técnicas de sensoriamento remoto. O MTR pode permitir a interpretação física da quantidade de reflectância medido por satélite, e pode ajudar a diferenciar as múltiplas fontes de variação do sinal de reflectância. O modelo DART - Discrete Anisotropic Radiative Transfer - é um dos modelos tridimensionais de transferência de radiação mais complexos, uma vez que utiliza uma abordagem matemática precisa e um grande realismo na simulação das paisagens. Seus principais resultados de simulação são a reflectância da cena (por exemplo, um povoamento florestal) em determinado comprimento de onda espectral em relação ao topo e à base da atmosfera, a simulação de imagens de satélite e a simulação do balanço de radiação. Apesar do potencial do DART na análise de parâmetros biofísicos de paisagens florestais a partir de dados de sensoriamento remoto, existem poucos estudos sobre sua aplicação em povoamentos florestais no Brasil; que podem dispor de um elevado número de medições de campo importantes para a parametrização do modelo. O principal objetivo deste estudo foi avaliar se o DART pode ajudar a compreender o comportamento da reflectância do dossel das plantações de eucalipto oriunda de dados de imagens de satélite e, em particular, se DART pode melhorar a estimativa do IAF ao invés do uso somente de modelos empíricos como índices espectrais da vegetação. O DART foi parametrizado com extensos dados de campo adquiridos em um experimento com testes clonais do Projeto Eucflux. Os objetivos específicos foram: i) parametrizar o modelo DART em diferentes idades e com diferentes materiais genéticos de plantações de eucalipto e comparar a reflectância simulada com imagens de satélite de alta resolução adquiridas no mesmo local; ii) analisar a relação entre o Índice de Área Foliar (IAF) e Índices Espectrais de Vegetação (IEV's) com base em relações empíricas, e, em seguida, usando o modelo DART; iii) analisar as vantagens e as limitações do uso de uma relação genérica ou uma relação específica do genótipo entre IAF e IV e encontrar outros critérios para agrupar os genótipos. No Capítulo 2 foi demonstrado bom desempenho do DART para simular a reflectância do dossel das florestas plantadas de eucalipto. As reflectâncias simuladas foram semelhantes com as obtidas pelas imagens de satélite de alta resolução, apesar de algumas discrepâncias encontradas na região do infravermelho próximo. No Capítulo 3, foi mostrado que as relações empíricas entre os IEV's e os IAF's foram capazes de estimar com razoável precisão para as relações genéricas dos plantios. Contudo, as estimativas por genótipo deram resultados superiores. A mesma metodologia foi aplicada em um conjunto de dados simulados pelo DART com as mesmas conclusões. Uma possibilidade intermediária de agrupar os genótipos foi em função das propriedades ópticas da serapilheira ou das folhas, com desempenhos intermediários. Nós concluímos sobre a superioridade do NDVI para estimar o LAI usando uma calibração específica para cada genótipo. Em termos mais gerais, os dados simulados com o modelo DART utilizados neste trabalho permitiram calibrar diferentes relações IAF-IEV em função dos genótipos, sensores e características de aquisição.

Palavras-chave: DART; Reflectância; Imagem de satélite; Plantações florestais

ABSTRACT

Three-dimensional modeling of radiative transfer and canopy reflectance in *Eucalyptus* stands

Radiative transfer models (RTM) have been successfully used to simulate the effect of forest structural and biochemical characteristics, such as tree sizes and shapes, leaf area index (LAI), leaf angle distribution (LAD), on the canopy radiative budget. One particular use of RTM is the analysis of the reflected light by the canopy, which can be measured by remote sensing techniques. RTM allows a physically based interpretation of the reflectance quantity measured by satellite and can help disentangling the multiple source of variation of the reflectance signal. The DART model - Discrete Anisotropic Radiative Transfer - is one of the most complex three-dimensional RTM, since it uses an accurate mathematical approach of physical processes and a great realism of the landscapes under simulation. Its main simulation outputs are the reflectance of the scene (e.g. a forest stand) at particular spectral wavelength from bottom and top of the atmosphere, the simulation of satellite images, and the simulation of localized radiative budget. Despite the DART potential in analyzing biophysical parameters from remote sensing data, few studies report its application in forest plantations in Brazil, which can have a large number of important field measurements to parameterize the model. The main objective of this project is to evaluate if the DART RTM can help understand the satellite-measured canopy reflectance of *Eucalyptus* plantations and in particular if DART RTM can improve LAI estimation rather than use only empirical models, as spectral vegetation indices. DART model was parameterized using extensive *in situ* data obtained from a clonal test, part of the EucFlux project. The specific objectives were: i) parameterize the DART model at different growth stages and for different clonal materials of *Eucalyptus* plantations and compare simulated reflectance with high resolution satellite images acquired on the same site; ii) analyze the relationship between the Leaf Area Index (LAI) and Spectral Vegetation Indices (SVI) based on empirical relationships, and then use the DART model; iii) analyze the advantage and drawbacks of using a generic relationship or a clone-specific relationship between LAI and SVI, and find other criteria for grouping the genotypes in the same. In Chapter 2, we demonstrated the good performance of DART to simulate canopy reflectance of *Eucalyptus* forest plantations. The simulated reflectance was similar to those measured by very high resolution images from satellite, despite some discrepancies found in the near infrared region. Then, in Chapter 3, we showed that empirical relationships between LAI and SVI were able to give a reasonable precision for generic relationships; however, genotype-scale relationships gave even better results. The same methodology applied on a DART simulated dataset lead to the same conclusions. An intermediate possibility of grouping the genotypes regarding their litter or leaf optical properties gave intermediate performance. We finally concluded about the superiority of NDVI to estimate LAI using a genotype-specific calibration. Overall, DART simulated datasets created in this work enable to calibrate different LAI -SVI relationships in terms of genotypes, sensors and acquisition characteristics.

Keywords: DART model; Reflectance; Satellite image; Forest plantations

1 INTRODUCTION

Brazilian forest plantations cover approximately 7.74 million ha, and 5.6 million ha are *Eucalyptus* plantations, representing 71.9 % of the total (INDÚSTRIA BRASILEIRA DE ÁRVORES - IBÁ, 2015). The area planted with *Eucalyptus* in Brazil is continuously increasing, for instance, there was an increase of 1.8 % in 2014 compared to 2013 (IBÁ, 2015). The expansion of fast-growing forest plantations in tropical and subtropical regions is related to the increasing global demand for forest products (FAO, 2007). In this context, in 2008, forest plantation areas were predicted to double by 2020, reaching ~9 MHa (BRASIL, 2008), mainly with *Eucalyptus* and *Pinus* species. However, the slowing down of Brazilian economic growth and the current economic crisis has revised down these projections for 2020. Conversely, this increase in plantation areas also represents a significant increase in carbon sequestration and greenhouse effect mitigation (CERRI et al., 2010).

Because of the economic importance of *Eucalyptus* plantations in Brazil, there is need to develop accurate and reliable methods to assess forest carbon stocks, understand and monitor their ecological process at large scales. Remote sensing is powerful technique to monitor and predict forest dynamics (MARSDEN et al., 2010), thus, the development of remote sensing applications has become an active research field (BAKER et al., 2010). Studies conducted by Roberts et al. (2007) and le Maire et al. (2011a) are examples of these possibilities as they explore the response in terms of spatial variability, biomass production and reactivity of ecosystems to disturbances in forestry-related activities by using passive and active sensors to estimate forest variables (e.g. LAI, crown structure).

A more comprehensive remote sensing approach includes the use of Radiative Transfer Models (RTM) to extract parameters from sensor data, which deals with simulations of light transfer within the canopy, interception and scattering, and can also simulate the canopy light reflected into the atmosphere, used to compute reflectance. This model has been developed to describe the interaction of electromagnetic energy with several canopy components at crown and leaf levels (KUUSK; NILSON, 2000), allowing to quantify the effect of several vegetation characteristics (e.g. biophysical or biochemical parameters) (GASTELLU-ETCHEGORRY et al., 2004a) over space and time. Given the direct influence of radiation regime on photosynthesis and growth processes, the expected advantage of this modeling is the exact distribution of intercepted and absorbed radiation by forest plantations, which can be associated to other ecophysiological models simulating, for instance, leaf photosynthesis.

Within the RTM domain, the physically based radiative transfer models can be considered the most effective and robust to simulate canopies in terms of their generalization ability and accuracy, mainly when compared to empirical models (KIMES et al., 2002). While empirical relationships allow quick assessment of forest parameters, tridimensional (3D) radiative transfer models, such as the Discrete Anisotropic Radiative Transfer (DART) model, which will be used in this thesis (GASTELLU-ETCHEGORRY; ZAGOLSKI; ROMIER, 1996), enables new domains of data evaluation, especially using high-resolution images and/or field measurements and optical properties of canopy components. Therefore, 3D reflectance canopy models can be used to analyze the effects of optical properties of different canopy elements (stem, leaves, twigs, soil, others) and their associations, along with different geometric sun and view directions.

Originally, the DART model was developed to simulate bidirectional reflectance (BRF) behavior, remote sensing images and radiation budget of natural landscapes (e.g. trees, grass, soil and water) in the visible and infrared regions. Its approach involves an accurate mathematical modeling of physical processes and realism of canopy simulations (http://www.cesbio.ups-tlse.fr/us/dart/dart_pourquoi.html), considering a robust earth-atmosphere system. Applications of DART in the forest domain meet the increasing demand to understand tree growth processes. The DART model could also be used to simulate remote sensing data, supporting sensor calibrations and evaluation of landscapes along different spatial-temporal scales and changing several calibration parameters, even for object properties (e.g. trees dimension and optical properties) and sensor characteristics (e.g. spectral and spatial resolution). Research on development of vegetation structure and canopy dynamics over large spatial and temporal scales is essential to predict the growth of *Eucalyptus* plantations and, consequently, to understand forest ecosystems. RTM approaches are suitable to address these issues, but they are still under explored, mainly in the context of Brazilian *Eucalyptus* plantations. In this thesis, we analyzed the accuracy of the DART model and its output on different clones and ages. We worked with high spatial resolution satellite images acquired at different dates along the period of analysis and with precisely field-measured structural, biophysical and biochemical parameters to provide robust analyses of the forest structure. This is necessary for a better understanding of carbon balance and water and nutrients dynamics.

A description of the main concepts and parameters addressed before is shown in the next topics.

1.1 Eucalyptus plantations in Brazil

Species of *Eucalyptus* genus are arboreal evergreen ‘tropical’ rainforest trees belonging to the myrtle family (Myrtaceae) endemic to Australia. This genus plays an important role to meet the world’s demand for woody products, accounting for 8% of the areas with productive planted forests worldwide and one third of tropical forest plantations (LACLAU et al., 2013). In Brazil, of the 7.74 million hectares cropped with forest plantations, 71.9 % is planted with *Eucalyptus* (IBÁ, 2015). Most eucalypt planted areas are concentrated in the southern and southeastern regions, because the main industries of forest segments (pulp and paper, wood panels, steel and processed wood) are based in these regions, and by favorable climate conditions.

Eucalypts plantations in Brazil started in 1904 with investments of the Paulista Railway Company and coordinated by Edmundo Navarro de Andrade (GONÇALVES et al., 2013). At first (around 1930), these plantations were primarily aimed at producing firewood used as fuel for locomotives and sleepers for railways and, in the 1950s, large plantations were established for charcoal production. The pulp and paper industry, in this period, adopted eucalypt as the main source of raw material (LEMOS, 2012). However, the significant increase of the *Eucalyptus* plantation areas in Brazil occurred between 1960s and 1980s, mainly as result of tax incentives for reforestation and forest-based industries, increasing the planted area to 3 million hectares. Afterward, the period between the years 1980 and 2000 was marked by the consolidation of the Brazilian forest sector, including breeding programs, gains in productivity, areas expansion, product diversification, and increase in competitiveness and increases of concerns with social and environmental issues.

The consequence of gains in productivity of the *Eucalyptus* genus was an increase of the Mean Annual Increment from $15 \text{ m}^3 \text{ ha}^{-1} \text{ yr}^{-1}$ in 1970s (QUEIROZ AND BARRICHELO, 2008) to $40.7 \text{ m}^3 \text{ ha}^{-1} \text{ yr}^{-1}$ in 2012 (ASSOCIAÇÃO BRASILEIRA DE PRODUTORES DE FLORESTAS PLANTADAS- ABRAF, 2013). This productivity increase was achieved, mainly, by new eucalypt populations developed from inter-specific crosses, especially between *E. grandis* and *E. urophylla* and, consequently, the use of cloning techniques to select superior individuals to be planted at commercial scale (LEMOS, 2012). In addition, there were significant advances in silvicultural practices, such as the use of minimum tillage, control of weeds, pests and diseases, judicious fertilization recommendation and better control of forest fires. As a consequence, since the year 2000, Brazil has earned the position of a major international player of the planted forest sector (GONÇALVES et al., 2013). Nowadays, eucalypts plantations are grown for 6-8 years before the first clearcutting,

followed by another plantation or by coppice rotation (1-4 years). The wood produced is used for different purposes: energy (electricity and charcoal), pulp and paper, and constructions, and rotations varying from 20-25 years to sawmill wood (GONÇALVES et al., 2008).

Despite these silvicultural and genetic improvements and the recognized role in the international market, it is still necessary to improve the understanding of eucalypt plantations. One of these issues refers to studies on the analysis of biophysical parameters that influence the ecophysiological processes and the ability to absorb radiation over different genetic materials.

1.2 Forest biophysical parameters

Forest stands can be characterized by several biophysical parameters collected directly or indirectly during field measurements, estimated by empirical relationships or extracted from remote sensing data. Some important parameters, linked to important processes in forest functioning, are: diameter at breast height (DBH), height, volume, biomass, leaf area index (LAI), leaf angle distribution (LAD), and fraction of absorbed photosynthetically active radiation (fAPAR). In this work, we will deal mainly with LAI and indirectly with LAD, as present below.

1.2.1 Leaf Area Index (LAI)

The leaf area index (LAI) is a critical vegetation structural parameter for applications in biogeosciences (ZHAO et al., 2011) and varies in terms of species, growth stage, site conditions, seasons and management practices (JONCKHEERE et al., 2004). This index was originally defined as the total one-sided area of photosynthetic tissue per unit ground surface area (WATSON, 1947). Although this definition is applicable for broad-leaved trees with flat leaves because both sides of a leaf have the same surface area, it is more problematic for needle and non-flat leaves, because the one-sided area is not clearly defined (JONCKHEERE et al., 2004). Other LAI definitions and interpretations have been proposed and the diversity comes mainly from the measurement techniques. These different definitions can result in significant differences between LAI values. Besides the Watson's definition, other possible LAI definitions are:

- i. one-sided LAI - half the total developed area of leaves per unit of horizontal ground surface area (CHEN; BLACK, 1992; LANG, 1991). This definition is therefore valid regardless of the vegetation element shape (WEISS et al., 2004) and topography, and is commonly used to represent the gas exchange potential (BARCLAY, 1998);

- ii. horizontally projected LAI – sum of the shadow areas that would be cast by each leaf in the canopy with a light source at infinite distance and vertical, (sum for all leaves in the canopy) (RUNNING et al., 1986), common in remote sensing applications since it represents the maximum leaf area that can be seen by sensors from overhead. However, it is lower than the “real” LAI, described above, because leaves are not all horizontal (LAD section below);
- iii. inclined projected or silhouette LAI - projected area of leaves considering individual leaf inclinations to horizontal in their natural position on tree (SMITH et al., 1991; STENBERG, 1996). It is useful to model the effects of light penetration through the canopy, light interception efficiency and remote sensing (BARCLAY, 1998); since it represents the area of intercepted light and that would be observed by a nadir view from above. The LAI value calculated with this function is between the two estimates before;
- iv. non-overlapping inclined project LAI - projected area of leaves while accounting for leaf inclinations, counting overlapping leaf areas only once (BARCLAY, 1998). It represents the proportion of ground obscured by foliage in a remotely acquired image. Generally, we do not call this a LAI, but we refer to it as “direct intercepting surface”. It is similar to the “fraction of intercepted direct radiation” (fIPAR when radiation is in the Photosynthetically Active Radiation).

LAI is directly related to gas vegetation exchange processes (GITELSON et al., 2014; CIGANDA et al., 2008) such as transpiration (CLEUGH et al., 2007; ROGERS, 2013), rainfall interception (GHIMIRE et al., 2012), thereby, it can be used in parameterization of dynamic models to estimate these variables. In particular, process-based ecophysiological models, such as MAESTRA (MEDLYN, 2004), use LAI directly as an input to simulate tree-scale photosynthesis and transpiration, together with meteorological variables and other structural variables. Different spatial and temporal scales of LAI quantification is therefore important (le MAIRE et al., 2012), allowing a better understanding of dynamic changes in productivity and climate impacts on forest ecosystems (ZHENG; MOSKAL, 2009). Another example is to use LAI to examine relationships between environmental stress factors and forest damage caused by insects (EKLUNDH et al., 2009).

Two main procedures can be used to estimate LAI: direct and indirect methods. Direct measurements are more accurate, but they have the disadvantage of being extremely time-consuming and labor intensive (FASSNACHT et al., 1994), making long-term monitoring of spatial and temporal large-scale hard to conduct. However, these procedures are still used to

validate indirect methods (JONCKHEERE et al., 2004) or they can be used in “simple” forest ecosystem like the *Eucalyptus* plantations under study. Some direct LAI measurements are leaf collection (harvesting and non-harvesting sampling) and planimetric and gravimetric techniques. Other measurements consist of measuring the length and diameter of each leaf, whose product is generally well correlated with individual leaf surface, or leaf counting or the use of an average leaf size, among others. Indirect ground-based LAI measurements can be divided into indirect contact of LAI measurements (inclined point quadrat and allometric techniques) and indirect non-contact measurements by the light transmission analysis (DEMON, ceptometer, LAI-2000, hemispherical canopy photography, and others). Detailed description of these methods are discussed in Fassnacht et al. (1994), Jonckheere et al. (2004) and Weiss et al. (2004). In eucalypt plantations, the LAI estimations are based on a direct measurement of the leaf area in a subset of trees of different sizes, which are used to calibrate a local allometric relationship further applied to the inventory.

1.2.2 Leaf Angle Distribution (LAD)

Leaf angle distribution is defined as the mathematical description of the angular orientation of leaves in the vegetation, represented as the probability of a leaf element to have its normal vector within a specified angle. Since a uniform distribution of leaf azimuth angles (ϕ_L) is adopted, LAD becomes the probability density function of the zenith angle (θ_L) of leaf normal (ZOU et al., 2014) (Figure 1).

Figure 1 - Leaf angle orientation and geometry
Source: <http://www2.geog.ucl.ac.uk>.

A set of mathematical LAD functions is commonly used to classify measured leaf angle distributions, such as: planophile, erectophile, plagiophile, extremophile, spherical, ellipsoidal, rotated ellipsoidal, spherical, elliptical and two-parameter beta distribution (CAMPBELL, 1990; DE WIT, 1965; KUUSK, 1995; WANG et al., 2007) (Figure 2).

Figure 2 - Types of leaf angle distributions
Source: <http://www2.geog.ucl.ac.uk>

Of these distributions, the erectophile has the largest mean zenith angle of leaf normal, while the planophile has the smallest. The other distributions present intermediate zenith angles between these first angles. The ellipsoidal and 2-parameter beta distribution has also been used in some studies (KUCHARIK et al., 1998; KUUSK, 1995; ZOU et al., 2014), which allows to parameterize the LAD to a given measured leaf distribution, instead of supposing *a priori* one of the well-defined distributions above mentioned. The ellipsoidal is the most widely used the function of leaf angle distribution. This distribution considers that the leaf angle density function is the same as the angle density function for the area on the ellipsoid surface (CAMPBELL, 1990) and it has gained extensively use as it provides a reasonably accurate description of empirical angle distributions of many different canopies. Besides, it is described by only a single parameter - the average leaf angle (ALA). Actually, a more accurate ellipsoidal distribution, the rotated ellipsoidal distribution has been used (THOMAS; WINNER, 2000; WANG et al., 2007). This distribution corresponds to an

ellipsoid in which small surface elements are rotated normally to the surface and better addresses the density of probability of zero at a zero inclination angle (THOMAS; WINNER, 2000).

This parameter is one of most important biophysical parameters to describe canopy structure and it is necessary to accurately estimate absorbed, reflected and transmitted radiation fluxes (ROSS, 1981). LAD is variable intra and inter-species (HUTCHISON et al., 1986) and exhibits spatial and temporal variability (WIRTH et al., 2001). LAD has an essential role to determine light competition between leaves, between trees within a canopy (HIKOSAKA; HIROSE, 1997), and therefore energy balance and microclimate (THANISAWANYANGKURA et al., 1997).

Direct LAD can be measured with mechanical clinometers in contact with leaf surfaces. However, this is time-consuming, laborious and demands careful field work in a large number of representative leaf surfaces. Alternative indirect measurements using 3D digitized canopy elements with specialized instrumentation (SINOQUET et al., 1998, 2005), also time-consuming. Faster laser scanning (HOSOI et al., 2011; HOSOI et al., 2009) has also been used, but these methodologies demand resources and computing time afterwards. A photographic method, based on analyzing digital images of leaves in the canopies, has been applied and shown fast and accurate results (PISEK et al., 2011; ZOU et al., 2014). Lang et al. (1985) proposed to extract LAD inverting the radiation transmitted through the canopy at different view angles; however, it was inaccurate due to the difficulty to distinguish between the effects of leaf angles on canopy transmittance from effects of other structural canopy parameters such as LAI. Huang et al. (2006) and Gao et al. (2003) have found good results using bidirectional canopy reflectance (section 1.2.4) models to retrieve leaf angle distribution.

1.2.3 Fraction of Absorbed Photosynthetically Active Radiation (fAPAR)

The fraction of Absorbed Photosynthetically Active Radiation (fAPAR) is defined as the fraction of incoming Photosynthetically Active Radiation (PAR) absorbed by green elements of the canopy. PAR is the solar radiation reaching the vegetation in the wavelength region between 0.4 - 0.7 μm (FAO, 2009), which is the wavelength useful for the photosynthesis process, that is, fAPAR, along with other variables, can be therefore linked quantitatively to photosynthesis. Thus, fAPAR can express the energy absorption capacity of the canopies, as shown in Equation 1 (GOWER et al., 1999):

$$fAPAR = [(PAR_{\downarrow AC} - PAR_{\uparrow AC}) - (PAR_{\downarrow BC} - PAR_{\uparrow BC})]/PAR_{\downarrow AC} \quad (1)$$

Where, $PAR_{\downarrow AC}$ and $PAR_{\uparrow AC}$ are, respectively, incident and reflected PAR above the canopy, and $PAR_{\downarrow BC}$ and $PAR_{\uparrow BC}$ are incident and reflected PAR below the canopy ($PAR_{\uparrow BC}$ is the PAR reflected by the soil).

The Global Terrestrial Observing System (GTOS) and the Global Climate Observing System (GCOS) state that fAPAR is one of the fundamental climate variables (ECVs), a critical parameter to analyze energy and carbon balance of ecosystems (FAO, 2008; PICKETT-HEAPS et al., 2014). It is directly linked to the photosynthesis process and, consequently, has been related to canopy chlorophyll content (ZHANG et al., 2009), canopy architecture (GUILLEVIC, 1999), and evapotranspiration rates. fAPAR is one of the few parameters that relate ecosystem function and structure (ASNER et al., 1998). Moreover, time series of fAPAR can be used to monitor vegetation and environmental indicators (GOBRON et al., 2006), drought events (GOBRON et al., 2005), land degradation (SENNA et al., 2005), phenology (VERSTRAETE et al., 2008), biodiversity (COOPS et al., 2008) as well as to retrieve radiation fluxes for climate modeling (PINTY et al., 2006).

The basic direct fAPAR measurement requires the use of PAR sensors to measure each flux of the equation (1), with several commercial instruments that have been built and used for ground-based fAPAR measurements (FAO, 2009). This direct *in-situ* determination can be a challenge in a heterogeneous forest ecosystem, since it requires simultaneous measurements of PAR above and within the canopy, adequate spatial sampling and daily average representative. As an alternative, many studies conducted on canopy light interception use the fraction of PAR intercepted by the canopy (fIPAR) instead of fAPAR, since it is easier to measure and provide almost the same value (GOWER et al., 1999).

1.3 Remote Sensing of forest stands

Many important ecological and silvicultural issues concern forest ecosystem processes in large areas. However, understanding the functions of forest stand has come fundamentally from intensively *in-situ* studies conducted in small experimental areas, due to the difficulty to conduct direct measurements at large temporal and spatial scales. In this context, remote sensing products are alternatives for assessments of large forest stands and offer potential to complement or even replace field measurements of forest stands in larger areas (HOMOLOVÁ et al., 2013; KOKALY et al., 2009). Remote sensing can be defined as the means to obtain information about an object without physical contact. According to Novo

(2010), in studies on terrestrial environment, remote sensing uses sensors and equipment for data processing to record and analyze interactions between incoming electromagnetic radiation and target objects on the earth's surface. In forestry, these objects are usually tree canopies and the gaps between canopies. Remote sensing data is collected using either passive or active sensors coupled on terrestrial, aerial or orbital platforms and represent a tradeoff among spatial, spectral and temporal resolutions (JENSEN, 2005). An illustration of active and passive sensors schemes are shown in Figure 3.

Figure 3 - Scheme of passive and active sensor systems
Source: <https://en.wikipedia.org/>.

Passive optical sensors are the most commonly used; however, radar images are also used in forestry. In general, optical sensors sample the reflected light in the shortwave part of the electromagnetic radiation spectrum, which includes the visible, near and middle infrared portions of the spectrum (350 up to 3000 nm). Some sensors also measure spectral bands in the long-wave part of the spectrum (i.e. thermal bands). Optical sensors can provide

quantitative and qualitative information on foliage and biochemical properties (ROBERTS et al., 2007), as described above. On the other hand, active sensors, such as LiDAR and radar, emit microwave pulses and record the backscatter from targets, providing information about biomass and forest structure (BOYD; DANSON, 2005).

Interactions between incident radiation and canopy forests elements are complex and are described by absorption, reflection and transmission of the group of leaves and other objects (e.g. twigs, branch) that compose the canopy. The intensity of this process depends of the physical-chemical properties of the objects and the intensity of the incident source. Reflectance is a property of a specific object to reflect the incident electromagnetic radiation and is expressed through reflectance factors (ρ) for given wavebands (PONZONI; SHIMABUKURO, 2007). The reflected radiation flux is also determined by the specific geometric characteristics of incident and reflected radiation and depending on these characteristics, these factors can be bidirectional (two geometries involved) in which one geometry is representative of the incident (radiation source, e.g. sun) azimuth and zenith angles. The other is characterized by the azimuth and zenith angles of the sensor that records intensity of the reflected flux (view angles). Reflectance can also be directional-hemispheric, which is measured by directional illumination and reflected radiation record using integrated spheres (PONZONI; SHIMABUKURO, 2007). The directional-hemispheric reflectance factor of a green leaf is presented in Figure 4, which can be characterized by a well-described absorption of foliar photosynthetic pigments (chlorophylls mainly) in the visible region (0.4 - 0.7 μm), leaf structure in the near infrared region (0.7 - 1.3 μm , NIR), and water and protein absorptions in the shortwave infrared region (1.3 - 2.5 μm , SWIR) (HOMOLOVÁ et al., 2013).

Figure 4 - Typical spectral reflectance curve for vegetation

Source: <http://www.scotland.gov.uk>

Studies on forest ecosystems using remote sensing techniques can benefit from a wide variety of data provided by different passive and active systems in different spectral, spatial and temporal resolutions. A summary of the ecological approaches and remote sensing spatial scales is shown in Figure 5. Satellite data have revolutionized the research to characterize and monitor vegetation dynamics at global scales by using, for example, vegetation indexes (NDVI, EVI, SR, among others, described in next section) and retrieving forest parameters. Information on the main operational satellites and their spatial, temporal and spectral resolutions can be found in Jensen (2005) and at <http://www.itc.nl/research/products/sensordb/searchsat.aspx>.

Figure 5 - Ecological and remote sensing spatial scales with examples of typical operational remote sensing spectroradiometers at different spatial scales

Source: Homolová et al. (2013).

LAI is one of the parameters that can be obtained using remote sensing images, from active or passive sensors, on board of terrestrial, aerial or spatial platforms. Estimations of LAI from satellites images in the visible part of the spectrum generally rely on spectral vegetation indices or radiative transfer model inversions (le MAIRE et al., 2012). These methods are based, mainly, on the use of spectral wavelength bands measured by satellite in the form of images (multispectral images if few broadband bands are measured, hyperspectral images if many narrow bands), in the visible spectrum (~350 to ~2500 nm). Some spectral bands (narrow or broad) are highly sensitive to vegetation structure, such as in the near infrared region. Other bands are linked to the canopy absorption by the chlorophyll, like in the red band. The combination of these bands in spectral vegetation indices (SVI) is therefore correlated to LAI, but this relation is highly dependent on the SVI used, vegetation type, among others. These aspects concerning SVI and Radiative Transfer Models inversion will be further discussed in this thesis. LAI retrieval using remote sensing tools are viable alternatives allowing assessments at large scales (NORTH, 2002) and have been considered an indispensable alternative to model and simulate ecological variables and processes at large scales. In the literature, several studies have reported different remote sensing techniques from more than 30 years (BANSKOTA et al., 2013; DELEGIDO et al., 2013; DUPUY et al., 2013; GITELSON et al., 2014; HERNÁNDEZ et al., 2014; le MAIRE et al., 2011a, 2012; MA et al., 2014; PROPASTIN, 2009).

As for LAI, empirical relationships calibrated between vegetation indices and field measurements are used to estimate fAPAR from satellite images (FENSHOLT et al., 2004). fAPAR can also be estimated from inversion of physically based radiation transfer models that use remote sensing data as input (D'ODORICO et al., 2014; FAO, 2009). Several spatial agencies and other institutional providers have created and delivered various fAPAR products at different temporal and spatial resolutions. However, *in situ* validation of fAPAR products and estimation of their uncertainty are seen as a critical task that remains incomplete (SEIXAS et al., 2009). Studies handling fAPAR products can be found in D'odorico et al., (2014), Gobron et al., (2008), Mccallum et al., (2010) and Pickett-Heaps et al., (2014).

In association with terrestrial land-surface models (HAVERD et al., 2013; KAMINSKI et al., 2012), remote sensing data can also be used to better understand carbon and water cycles (PICKETT-HEAPS et al., 2014).

1.4 Spectral Vegetation Indices (SVI's)

Canopy properties can be analyzed by empirical and physical remote sensing models (HOMOLOVÁ et al., 2013). Empirical methods are based on statistical relationships between field data collection and remote sensing data using regression techniques (SMITH et al., 2002). The sensitivity analysis of remote sensing data toward properties of interests is often improved by calculating vegetation indices (CHEN et al., 2010) or spectral transformations in case of contiguous hyperspectral data (SCHLERF et al., 2010).

Over the last decades, many remote sensing issues have been focused on collecting information on spectral measurements to characterize the presence and quality of vegetation elements, extracting and modeling several biophysical parameters from vegetation targets (BARET et al., 1987; DARVISHZADEH et al., 2008b; SCHLERF et al., 2005; WANG et al., 2005). Most of these efforts have used Spectral Vegetation Indices (SVI's), dimensionless radiometric metrics that indicate the relative abundance and green vegetation activity (JENSEN, 2005) and estimate spatiotemporal variations in the biophysical and biochemical parameters of vegetation, such as LAI, percentage of vegetation cover, fraction of absorbed photosynthetically active radiation (fAPAR), canopy chlorophyll content, estimating and forecasting crop yields, crop type and conditions (DELEGIDO et al., 2013; LE MAIRE et al., 2008, 2011a, 2011b, 2012; LIANG et al., 2015; WU; NIU; GAO, 2012; ZHAO et al., 2007).

SVI's were developed based on the characteristics of the vegetation reflectance along the spectrum. These characteristics can be primarily determined by pigments, especially chlorophyll concentration, influencing the vegetation reflectance spectra mainly in the visible

domain, such as in the blue, green and red regions of the spectrum. The near-infrared (NIR) region is also important to analyze vegetation reflectance and is determined by the arrangement of cells within the mesophyll layer of leaves (influence of leaf reflectance) and by canopy structure (e.g. LAI). An ideal SVI for vegetation parameter retrieval should be well correlated for these biophysical parameters in a wide range of vegetation conditions. It should minimize external and internal effects and differences related to non-photosynthetic components and senescent leaves. It is also related to some field measurable parameters for validation and quality control purposes (JENSEN, 2005; LIANG et al., 2015), e.g. canopy structure, average leaf angle and others.

One of the main advantages of these SVI's is that they allow obtaining relevant information about vegetation cover in wide areas and over time in a fast and easy way, besides, the underlying mechanisms are well-understood (DELEGIDO et al., 2013). However, SVI's lack cause-effect relationships and, consequently, the statistical predictions often suffer from lack of robustness and transferability as they are usually site, species and time specific (COLOMBO et al., 2003). Several SVI's have been developed over the last decades, some are more generalists, while others are more specific for species and local conditions (e.g. EucVI developed for LAI retrieval in eucalypt plantations, described in le Maire et al.(2012). These SVI's are primarily constructed using the inverse relationship between the red and NIR spectral regions. A summary of some of these SVI's is shown in Table 1.

Table 1 - Summary of some spectral vegetation index

Vegetation Index	Equation	Reference
Simple Ratio (SR)	$SR = \frac{\rho_{NIR}}{\rho_{RED}}$	Birth and Mcvey et al., 1968
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$	Rouse et al., 1973
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{(1 + L^*)(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED} + L^*)}$	Huete, 1988
Enhanced Vegetation Index (EVI)	$EVI = G^{**} \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1^{**} \rho_{RED} - C_2^{**} \rho_{BLUE} + L^{**}}$	Wang et al., 2002
Optimized Soil Adjusted Vegetation Index (OSAVI)	$OSAVI = \frac{(1 + 0.16)(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED} + 0.16)}$	Rondeaux et al., 1996

* $L = 0.5$; ** $G = 2.5$, $C_1 = 6.0$, $C_2 = 7.5$ and $L = 1.0$

The most widely known is the Normalized Difference Vegetation Index (NDVI) (ROUSE et al., 1973), which uses a normalized difference between red and near-infrared regions. NDVI has been used to monitor vegetation activity over annual and seasonal growth stages and is strongly correlated with LAI. However, since the relationship between NDVI and LAI is exponential, NDVI often shows saturation under conditions of moderate-to-high

LAI values (e.g. $> 3 - 5$) (HABOUDANE, 2004; WANG et al., 2005). Other VI commonly used is the Soil Adjusted Vegetation Index (SAVI), the Enhanced Vegetation Index (EVI) and the Optimized Soil Adjusted Vegetation Index (OSAVI). More detailed description about vegetation index can be found in JENSEN(2005).

1.5 Radiative Transfer Models of vegetation

Physical remote sensing is another method to retrieve biophysical parameters of forest canopies. This method is based on radiative transfer models (RTM). This kind of model simulates light absorption and scattering inside vegetation canopies using the leaf biochemical composition and canopy structural properties as input (GASCON et al., 2004; JACQUEMOUD et al., 2009; LAURENT et al., 2011b). Several types of different RTM use a variety of robust and precise mathematical and computational representations of the radiation transfer in the environment (terrestrial and atmosphere surfaces) (GASTELLU-ETCHEGORRY, 2013). These models can be relatively simple or complex, requiring different input parameters to address the entire radiative transfer problem in order to simulate the vegetation reflectance for any experimental conditions.

Radiative transfer models (RTM) of canopies have been approved as effective tools for the retrieval of vegetation canopy biochemical/biophysical characteristics from remote sensing data, for example, the leaf area index (DARVISHZADEH et al., 2008a; HOUBORG; BOEGH, 2008; HOUBORG et al., 2007; KOBAYASHI et al., 2007; MYNENI, 1997), chlorophyll content (HOUBORG; BOEGH, 2008; MALENOVSKÝ et al., 2007, 2013) and leaf water content (CHENG et al., 2008; COLOMBO et al., 2008; TROMBETTI et al., 2008). Other canopy structural properties (e.g., leaf aggregation, leaf angle distribution, clumping at different scales) present a substantial challenge for RTMs parameterization and interpretation from RS data and need to be further investigated(OLLINGER, 2011).

Normally, the application of RTM to recover canopy parameters uses the inversion methods that identify the set of parameters of the model that provides the best fit between the simulated reflectance and the remote sensing reflectance. The accuracy of inversion is associated with the inversion method and the characteristics of remote sensing measurements (radiometric and spatial resolution, view direction, spectral domain, among others). Due to the complexity of RTMs, the inversion procedure is not straightforward (LAURENT et al., 2011a). Many inversion methods are available and can be divided into three major categories (KIMES et al., 2000): 1) traditional inversion methods that minimize the distance between simulations and measurements through minimization of algorithms, 2) Look-up table (LUT)

methods, where a dataset of possible reflectance is pre-computed, 3) and machine learning methods, for example, Neural Networks and Random Forest, which use non-linear a non-parametric regression between reflectance and parameters, calibrated on a simulation dataset. The first method is robust but computationally intensive and not appropriate to deal with large sets of remote sensing data. Then, the other two methods are potentially more efficient and accurate, since they can use complex reflectance models with acceptable computational time and do not require initial guesses to model parameters as traditional inversion methods do (GRAU; GASTELLU-ETCHEGORRY, 2013). Other interesting methods can be the calibration of vegetation indices and the model regression (le MAIRE et al., 2008)

The Look-up table is one of most applied methods to remote sensing data inversion (GASTELLU-ETCHEGORRY et al., 2003; KIMES et al., 2002; LIANG et al., 2006). This method consists in a pre-computed table of reflectance simulations for a set of values of input parameters in the model that sample all possible values (GASTELLU-ETCHEGORRY, 2013). This method can be fast because the most computationally expensive part of the inversion procedure is completed before the inversion itself. Thus, it is well suited to computationally expensive complex 3-D reflectance models (GRAU; GASTELLU-ETCHEGORRY, 2013).

Radiative transfer models of forest canopies can also be classified according to their properties associated with interception of incident radiation as: isotropic media, azimuthally isotropic media and anisotropic media (VERHOEF, 1998). For the isotropic media, radiation interception is independent from the incident direction (e.g. canopies with spherical leaf angle distribution). For the azimuthally isotropic media, radiation interception is independent from the azimuth angle, but it depends on the incident direction of the zenith angle (e.g. canopies with other LAD than spherical). Finally, in the anisotropic media, radiation interception depends on both the azimuth and zenith angles (e.g. heterogeneous forest canopies). Other types of specific classifications of radiative transfer models can be found in (VERHOEF, 1998). An intercomparison of well-established radiation transfer model can be accessed in the RAMI initiative (<http://rami-benchmark.jrc.ec.europa.eu/HTML/>).

The radiative transfer within a canopy usually depends on the spatial distribution of canopy elements and subsequent complex radiative processes, such as the multiple scattering, mutual shading of crowns and background shading (KOETZ et al., 2004). To simulate these complex light-element interactions, three-dimensional canopy radiative transfer models are required. This is especially the case for heterogeneous canopy structure (GASTELLU-ETCHEGORRY et al., 2003; GASTELLU-ETCHEGORRY; TRICHON, 1998; KOETZ et

al., 2004). The major drawback of these physical methods is that different combinations of RTM input parameters may produce the same reflectance spectra, which makes estimation of canopy properties by RTM inversion difficult (COMBAL et al., 2002).

1.6 DART model

The DART - "Discrete Anisotropic Radiative Transfer" - model is an RTM that simulates, in wavelengths of the optical domain, the radiative transfer of homogeneous and heterogeneous landscapes in 2 or 3 dimensions by ordinary and exact kernel methods (GRAU; GASTELLU-ETCHEGORRY, 2013). It uses an iterative approach, that is, intercepted radiation i is scattered at iteration $i + 1$. DART landscapes, defined in the model as "scenes", are voxels (arrays of cells) when the elements that compose the scenes are simulated as a 3D juxtaposition of rectangular cells (Δx , Δy , Δz) that contain turbid material and/or planar elements (e.g. triangles) (CENTRE D'ETUDES SPATIALES DE LA BIOSPHERE - CESBIO, 2013b) (Figure 6).

Figure 6- Representation of Earth-Atmosphere system DART simulation. Atmosphere comprises three regions: upper (HA), middle (MA) and bottom (BA). The simulated landscape (scene) is inserted at the bottom part of the atmosphere

Source: CESBIO (2013)

Several bands (visible to thermal infrared) can be computed in a single simulation with three methods: flux tracking, Monte Carlo and LiDAR. The flux tracking method, also known as "ray tracing", has three modes: 'R' (reflectance), which simulates the reflectance using the

sun and/or atmosphere as radiation sources; 'T' (thermal), which simulates brightness temperature using the atmosphere and Earth scene as radiation source; and 'R + T' (reflectance and thermal), which simulates temperature brightness using the sun, Atmosphere and Earth scene as radiation source. The Monte Carlo method works only with the 'R' mode and without atmosphere. The LiDAR method is an active method and simulates only scattering processes (no thermal emission).

The cells that compose the scene array can contain turbid materials and triangles (GRAU; GASTELLU-ETCHEGORRY, 2013). Turbid material is used to simulate interactions of three-dimensional (3D) (vegetation and fluids, e.g. air and water) with scattered radiation obeying the Beer's law (ROSS, 1981). In this concept, the tree crowns are considered juxtapositions of turbid material cells and surfaces simulation (trunks, branches, topography, etc.) are computed as triangles. Using the modeling of the radiative transfer of the scenes, this model can generate results like remotely sensed images, land cover maps, energy budget (temperature, fAPAR, CO₂ assimilation, and transpiration), and LiDAR waveforms, among others.

The simulated atmosphere in the scene is composed of cells in three regions (BA, MA and HA, as shown in Figure 6) and its size increases as the altitude increases. Radiation propagates in a finite number of directions Ω_i with an angular sector width $\Delta\Omega_i$. Any set of N discrete directions may be used (not necessarily equal solid angles, but $\sum_{n=1}^N \Delta\Omega_n = 4\pi$) (GASTELLU-ETCHEGORRY, 2008). Scattered radiation along the direction Ω_i at a position r is known as a source vector $W(r, \Omega_i)$. Radiation interaction in the atmosphere corresponds to absorption and not-resonant (scattering, thermal emission) mechanisms that depend on radiation (e.g. wavelength) and atmosphere (gas and aerosol volume density N , pressure P and temperature T) (CESBIO, 2013a). In DART, the atmospheric parameters can be manually input by the operator or specified using pre-computed databases (most accurate approach) that store information derived from the Lowtran and Modtran atmosphere models (BERK, 1989). These models simulate the atmosphere as a layer consisting of gases, aerosols, rain and other particles with vertical profiles (temperature, concentration) and specific optical properties. More theoretical DART details can be found in Gastellu-Etchegorry et al. (1999) and Gastellu-Etchegorry et al. (2004).

The DART model works with a graphical user interface (GUI) for input parameters that describes the landscape and illumination scene conditions. This interface uses four basic modules ("Direction" - calculates and stores the sun and view directions; "Phase" - calculates the general properties of the scene; "Maket" - scene geometry and landscape dimensions; and

"Dart" - pre-computes light beam and simulates radiation propagation) and five optional modules ("Vegetation", "SequenceLauncher", "DEMGenerator", "Hapke" and "PROSPECT") (CESBIO, 2013b). An example of input parameters and modeling scheme is presented in Figure 7.

Figure 7 - Scheme of DART parameterization and simulation on mode R of the flux tracking method. Hollow rectangles represent the input parameters and gray geometric forms and arrows represent the DART simulation process

Source: Adapted from CESBIO (2013a)

Since its first release in 1996, DART has been successfully tested in studies on canopy vegetation compared with field measurements, such as impact of canopy structure on satellite images texture (BRUNIQUEL-PINEL; GASTELLU-ETCHEGORRY, 1998) and reflectance (GASTELLU-ETCHEGORRY, 2008), three-dimensional distribution of photosynthesis and primary production rates of canopies (MALENOVSKÝ et al., 2007), influence of wood

elements of spruce canopy on nadir reflectance (MALENOVSKY et al., 2008), classification of heterogeneous forests (COUTURIER et al., 2009), quantification of chlorophyll leaves content (MALENOVSKÝ et al., 2013), among others. DART is one of the most complex three-dimensional radiation transfer models (KIMES et al., 2002). It has been continuously improved in terms of accuracy, scenes modeling (topography, vertical and horizontal trees canopy structure), radiative transfer (LiDAR, scene spectrum, band sensors) and functionality (SQL database) (GRAU; GASTELLU-ETCHEGORRY, 2013).

1.7 Objectives of the Thesis

The main hypothesis of this thesis was that interaction of radiation simulation between solar radiation and canopy, the three-dimensional radiative transfer models (DART), allows quantifying biophysical parameters and structural characteristics of forest canopies and evaluating canopy reflectance of satellite images.

The main objective of this thesis was to analyze canopy reflectance of *Eucalyptus* plantations under different genotypes and ages using the DART radiative transfer model to simulate remote sensing data obtained from satellite images in visible and near infrared spectral bands.

The specific objectives were to:

- 1) Parameterize the DART model at different ages and genotypes of *Eucalyptus* plantations and analyze the accuracy of simulated images by comparing the reflectance on top of atmosphere with real very high-resolution satellite images. Hypothesis: Reflectance in *Eucalyptus* plantations varies according to stand age and genotype composition and these differences can be simulated using the DART (Discrete Anisotropic Radiative Transfer) model obtained from real satellite images;
- 2) Analyze the relationship between the Leaf Area Index (LAI) and different Spectral Vegetation Indices (SVI's) using empirical methods and DART simulated images over a variety of acquisition configurations, ages and genotypes of *Eucalyptus* stands. Hypothesis: Accuracy of relationships between spectral vegetation indices and the leaf area index is improved using the hybrid method with SVI's and RTM to account for stand properties and satellite acquisition conditions effects.

1.8 Thesis Structure

The thesis was structured in two chapters, organized according to specific objectives. The articles had, as general approaches, the topics:

- Paper 1: Accuracy of DART model to simulate very high spatial resolution satellite images of *Eucalyptus* stands at different ages and genotypes materials.
- Paper 2: Relationship between the leaf area index and spectral vegetation indices in *Eucalyptus* stands using simulated images with very high spatial resolution from the DART model.

References

ASNER, G.P.; WESSMAN, C.A.; ARCHER S. Scale dependence of absorption of photosynthetically active radiation in terrestrial ecosystems. **Ecological Applications**, Tempe, v. 8, n. 4, p. 1003–1021, 1998.

ASSOCIAÇÃO BRASILEIRA DE PRODUTORES DE FLORESTAS PLANTADAS. **Anuário Estatístico ABRAF ano base 2012**. Brasília, 2012.

BAKER, D.J.; RICHARDS, G.; GRAINGER, A.; GONZALEZ, P.; BROWN, S.; DEFRIES, R. Achieving forest carbon information with higher certainty: A five-part plan. **Environmental Science & Policy**, Exeter, v. 13, n. 3, p. 249–260, 2010.

BANSKOTA, A.; WYNNE, R.; THOMAS, V.; SERBIN, S.; KAYASTHA, N.; GASTELLU-ETCHEGORRY, J-P.; TOWNSEND, P. Investigating the utility of wavelet transforms for inverting a 3-D radiative transfer model using hyperspectral data to retrieve forest LAI. **Remote Sensing**, Lower Hutt, v. 5, n. 6, p. 2639–2659, May 2013.

BARCLAY, H.J. Conversion of total leaf area to projected leaf area in lodgepole pine and Douglas-fir. **Tree physiology**, Oxford, v. 18, n. 3, p. 185–193, Mar. 1998.

BARET, F.; CHAMPION, I.; GUYOT, G.; PODAIRE, A. Monitoring wheat canopies with a high spectral resolution radiometer. **Remote Sensing of Environment**, New York, v. 22, n. 3, p. 367–378, Aug. 1987.

BERK, A. **Modtran**: a moderate resolution model for Lowtran 7. 1989.

BIRTH, G.S.; MCVEY, G.R. Measuring the color of growing turf with a reflectance spectrophotometer. **Agronomy Journal**, Madison, v. 60, n. 6, p. 640–643, 1968.

BOYD, D.S.; DANSON, F.M. Satellite remote sensing of forest resources: three decades of research development. **Progress in Physical Geography**, London, v. 29, n. 1, p. 1–26, Jan. 2005.

BRASIL. Governo Federal - Comitê Interministerial sobre Mudança. **Plano Nacional sobre Mudança do Clima (PNMC)**. Brasília, 2008.

BRUNIQUÉL-PINEL, V.; GASTELLU-ETCHEGORRY, J-P. Sensitivity of texture of high resolution images of forest to biophysical and acquisition parameters. **Remote Sensing of Environment**, New York, v. 65, p. 61–85, Jan. 1998.

CAMPBELL, G.S. Derivation of an angle density function for canopies with ellipsoidal leaf angle distributions. **Agricultural and Forest Meteorology**, Amsterdam, v. 49, p. 173–176, 1990.

CENTRE D'ETUDES SPATIALES DE LA BIOSPÈRE. **DART handbook**. Toulouse, 2013a. 97p.

_____. **DART modules user manual**. Toulouse, 2013b. 54p.

_____. **DART user manual**. Toulouse, 2014. 142 p.

CERRI, C.C.; BERNOUX, M.; MAIA, S.M.F.; CERRI, C.E.P.; COSTA JUNIOR, C.; FEIGL, B.J.; FRAZÃO, L.A.; MELLO, F.F.C.; GALDOS, M.V.; MOREIRA, C.S.; CARVALHO, J.L.N. Greenhouse gas mitigation options in Brazil for land-use change, livestock and agriculture. **Scientia Agricola**, Piracicaba, v. 67, p. 102–116, Jan./Feb.2010.

CHEN, J.M.; BLACK, T.A. Defining leaf area index for non-flat leaves. **Plant, Cell & Environment**, Oxford, v. 15, n. 4, p. 421–429, May 1992.

CHEN, P.; HABOUDANE, D.; TREMBLAY, N.; WANG, J.; VIGNEAULT, P.; LI, B. New spectral indicator assessing the efficiency of crop nitrogen treatment in corn and wheat. **Remote Sensing of Environment**, New York, v. 114, n. 9, p. 1987–1997, Sept. 2010.

CHENG, Y-B.; USTIN, S.L.; RIAÑO, D.; VANDERBILT, V.C. Water content estimation from hyperspectral images and MODIS indexes in Southeastern Arizona. **Remote Sensing of Environment**, New York, v. 112, n. 2, p. 363–374, Feb. 2008.

CIGANDA, V.; GITELSON, A.; SCHEPERS, J. Vertical profile and temporal variation of chlorophyll in maize canopy: quantitative “crop vigor” indicator by means of reflectance-based techniques. **Agronomy Journal**, Madison, v. 100, n. 5, p. 1409, 2008.

CLEUGH, H.A.; LEUNING, R.; MU, Q.; RUNNING, S.W. Regional evaporation estimates from flux tower and MODIS satellite data. **Remote Sensing of Environment**, New York, v. 106, n. 3, p. 285–304, 2007.

COLOMBO, R.; BELLINGERI, D.; FASOLINI, D.; MARINO, C.M. Retrieval of leaf area index in different vegetation types using high resolution satellite data. **Remote Sensing of Environment**, New York, v. 86, n. 1, p. 120–131, 2003.

COLOMBO, R.; MERONI, M.; MARCHESI, A.; BUSETTO, L.; ROSSINI, M.; GIARDINO, C.; PANIGADA, C. Estimation of leaf and canopy water content in poplar plantations by means of hyperspectral indices and inverse modeling. **Remote Sensing of Environment**, New York, v. 112, n. 4, p. 1820–1834, Apr. 2008.

COMBAL, B.; BARET, F.; WEISS, M.; TRUBUIL, A.; MACÉ, D.; PRAGNÈRE, A.; MYNENI, R.; KNYAZIKHIN, Y.; WANG, L. Retrieval of canopy biophysical variables from bidirectional reflectance using prior information to solve the ill-posed inverse problem. **Remote Sensing of Environment**, New York, v. 84, p. 1–15, 2002.

COOPS, N.C.; WULDER, M.; DURO, D.C.; HAN, T.; BERRY, S. The development of a Canadian dynamic habitat index using multi-temporal satellite estimates of canopy light absorbance. **Ecological Indicators**, Amsterdam, v. 8, n. 5, p. 754–766, Sept. 2008.

COUTURIER, S.; GASTELLU-ETCHEGORRY, J-P.; PATIÑO, P.; MARTIN, E. A model-based performance test for forest classifiers on remote-sensing imagery. **Forest Ecology and Management**, Amsterdam, v. 257, n. 1, p. 23–37, Jan. 2009.

DARVISHZADEH, R.; SKIDMORE, A.; ATZBERGER, C.; van WIEREN, S. Estimation of vegetation LAI from hyperspectral reflectance data: Effects of soil type and plant architecture. **International Journal of Applied Earth Observation and Geoinformation**, Enschede, v. 10, n. 3, p. 358–373, 2008a.

DARVISHZADEH, R.; SKIDMORE, A.; SCHLERF, M.; ATZBERGER, C. Inversion of a radiative transfer model for estimating vegetation LAI and chlorophyll in a heterogeneous grassland. **Remote Sensing of Environment**, New York, v. 112, n. 5, p. 2592–2604, May 2008b.

NOVO, E.L.M. **Sensoriamento remoto: princípios e aplicações**. Blucher, 2010.

DE WIT, C. **Photosynthesis of leaf canopies**. Wageningen: Center for Agricultural Publication and Documents, 1965.

DELEGIDO, J.; VERRELST, J.; MEZA, C.M.; RIVERA, J.P.; ALONSO, L. MORENO, J. A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems. **European Journal of Agronomy**, Amsterdam, v. 46, p. 42–52, Apr. 2013.

D'ODORICO, P.; GONSAMO, A.; PINTY, B.; GOBRON, N. COOPS, N.; MENDEZ, E.; SCHAEPMAN, M.E. Intercomparison of fraction of absorbed photosynthetically active radiation products derived from satellite data over Europe. **Remote Sensing of Environment**, New York, v. 142, p. 141–154, Feb. 2014.

DUPUY, S. LAINÉ, G.; TASSIN, J. SARRAILH, J-M. Characterization of the horizontal structure of the tropical forest canopy using object-based LiDAR and multispectral image analysis. **International Journal of Applied Earth Observation and Geoinformation**, Enschede, v. 25, p. 76–86, Dec. 2013.

EKLUNDH, L.; JOHANSSON, T.; SOLBERG, S. Mapping insect defoliation in Scots pine with MODIS time-series data. **Remote Sensing of Environment**, New York, v. 113, n. 7, p. 1566–1573, July 2009.

FAO. **Terrestrial essential climate variables**: for climate change assessment, mitigation and adaptation. Rome, 2008.

_____. **Assessment of the status of the development of the standards for the terrestrial essential climate variables**: fraction of absorbed photosynthetically active radiation. Rome, 2009.

FASSNACHT, K.S.; GOWER, S.T.; NORMAN, J.M.; MCMURTRIE, R.E. A comparison of optical and direct methods for estimating foliage surface area index in forests. **Agricultural and Forest Meteorology**, Amsterdam, v. 2000, n. 94, p. 183–207, 1994.

FENSHOLT, R.; SANDHOLT, I.; RASMUSSEN, M.S. Evaluation of MODIS LAI, fAPAR and the relation between fAPAR and NDVI in a semi-arid environment using in situ measurements. **Remote Sensing of Environment**, New York, v. 91, n. 3-4, p. 490–507, June 2004.

GAO, F.; SCHAAF, C.B.; STRAHLER, Y.; JIN, X.LI. Detecting vegetation structure using a kernel-based BRDF model. **Remote Sensing of Environment**, New York, v. 86, n. 2, p. 198–205, 30 July 2003.

GASCON, F.; GASTELLU-ETCHEGORRY, J-P.; LEFEVRE-FONOLLOSA, M.J.; DUFRENE, E. Retrieval of forest biophysical variables by inverting a 3-D radiative transfer model and using high and very high resolution imagery. **International Journal of Remote Sensing**, Basingstoke, v. 25, n. 24, p. 5601–5616, Dec. 2004.

GASTELLU-ETCHEGORRY, J-P. 3D modeling of satellite spectral images, radiation budget and energy budget of urban landscapes. **Meteorology and Atmospheric Physics**, Wien, v. 102, n. 3/4, p. 187–207, Dec. 2008.

_____. **Le rayonnement, sa mesure et son rôle modélisation du transfert radiatif**. Toulouse: CESBIO; Université Paul Sabatier, 2013.

GASTELLU-ETCHEGORRY, J.-P.; TRICHON, V. A modeling approach of PAR environment in a tropical rain forest in Sumatra: application to remote sensing. **Ecological Modelling**, Amsterdam, v. 108, n. 1/3, p. 237–264, May 1998.

GASTELLU-ETCHEGORRY, J.-P.; GASCON, F.; ESTÈVE, P. An interpolation procedure for generalizing a look-up table inversion method. **Remote Sensing of Environment**, New York, v. 87, n. 1, p. 55–71, Sept. 2003.

GASTELLU-ETCHEGORRY, J.-P.; MARTIN, E.; GASCON, F. DART: a 3D model for simulating satellite images and studying surface radiation budget. **International Journal of Remote Sensing**, Basingstoke, v. 25, n. 1, p. 73–96, Jan. 2004.

GASTELLU-ETCHEGORRY, J.-P.; ZAGOLSKI, F.; ROMIER, J. A simple anisotropic reflectance model for homogeneous multilayer canopies. **Remote Sensing of Environment**, New York, v. 57, p. 22–38, 1996.

GASTELLU-ETCHEGORRY, J-P.; GUILLEVIC, P.; ZAGOLSKI, F.; DEMAREZ, V.; TRICHON, V.; DEERING, D.; LEROY, M. Modeling BRDF and radiation regime of boreal and tropical forests: I. BRDF. **Remote Sensing of Environment**, New York, v. 316, p. 281–316, July 1999.

GHIMIRE, C.P.; BRUIJNZEEL, L.A.; LUBCZYNSKI, M.W.; BONELL, M. Rainfall interception by natural and planted forests in the Middle Mountains of Central Nepal. **Journal of Hydrology**, Amsterdam, v. 475, p. 270–280, Dec. 2012.

GITELSON, A.; PENG, YI; ARKEBAUER, T.J.; SCHEPERS, J. Relationships between gross primary production, green LAI, and canopy chlorophyll content in maize: implications for remote sensing of primary production. **Remote Sensing of Environment**, New York, v. 144, p. 65–72, Mar. 2014.

GOBRON, N.; PINTY, B.; MÉLIN, F.; TABERNER, M.; VERSTRAETE, M.M.; BELWARD, A.; LAVERGNE, T.; WIDLOWSKI, J-L. The state of vegetation in Europe following the 2003 drought. **International Journal of Remote Sensing**, Basingstoke, v. 26, n. 9, p. 2013–2020, May 2005.

GOBRON, N.; PINTY, B.; MÉLIN, F.; TABERNER, M.; VERSTRAETE, M.M.; BELWARD, A.; LAVERGNE, T.; WIDLOWSKI, J-L. Evaluation of fraction of absorbed photosynthetically active radiation products for different canopy radiation transfer regimes: Methodology and results using Joint Research Center products derived from SeaWiFS against ground-based estimations. **Journal of Geophysical Research**, Washington, v. 111, n. D13, 2006.

GOBRON, N.; PINTY, B.; AUSSEDT, O.; TABERNER, M.; FABER, O.; MELIN, F.; LAVERGNE, T.; ROBUSTELLI, M.; SNOEIJ, P. Uncertainty estimates for the FAPAR operational products derived from MERIS — Impact of top-of-atmosphere radiance uncertainties and validation with field data. **Remote Sensing of Environment**, New York, v. 112, n. 4, p. 1871–1883, Apr. 2008.

GONÇALVES, J.L.M.; STAPE, J.L.; LACLAU, J-P.; BOUILLET, J-P; RANGER, J. Assessing the effects of early silvicultural management on long-term site productivity of fast-growing eucalypt plantations: the Brazilian experience. **Southern Forests: a Journal of Forest Science**, Grahamstown, v. 70, n. 2, p. 105–118, Aug. 2008.

GONÇALVES, J.L.M.; ALVARES, C.A.; HIGA, A.R.; SILVA, L.D.; ALFENAS, A.C.; STAHL, J.F.; FERRAZ, S.F.B; LIMA, W.P; BRANCALION, P.H.S.;HUBNER, A.; BOUILLET, J-P.; LACLAU, J-P.; NOUVELLON, Y.; EPRON, D. Integrating genetic and silvicultural strategies to minimize abiotic and biotic constraints in Brazilian eucalypt plantations. **Forest Ecology and Management**, Amsterdam, v. 301, p. 6–27, Aug. 2013.

GOWER, S.T.; KUCHARIK, C.J.; NORMAN, J.M. Direct and indirect estimation of leaf area index , fapar , and net primary production of terrestrial ecosystems. **Remote Sensing of Environment**, New York, v. 70, p. 29–51, 1999.

GRAU, E.; GASTELLU-ETCHEGORRY, J-P. Radiative transfer modeling in the earth–atmosphere system with DART model. **Remote Sensing of Environment**, New York, v. 139, p. 149–170, Dec. 2013.

GUILLEVIC, P. Modeling BRF and radiation regime of boreal and tropical forest: II. PAR Regime. v. 340, p. 317–340, July1999.

HABOUDANE, D. Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. **Remote Sensing of Environment**, New York, v. 90, n. 3, p. 337–352, Apr. 2004.

HAVERD, V.; RAUPACH, M.R.; BRIGGS, P.R.; CANADELL, J.G.; ISAAC, P.; PICKETT-HEAPS, C.; ROXBURGH, S.H.; VAN GORSEL, E.; VISCARRA ROSSEL, R.A.; WANG, Z. Multiple observation types reduce uncertainty in Australia's terrestrial carbon and water cycles. **Biogeosciences**, Hoboken, v. 10, n. 3, p. 2011–2040, 25 Mar. 2013.

HERNÁNDEZ, C.; NUNES, L.; LOPES, D.; GRAÑA, M. Data fusion for high spatial resolution LAI estimation. **Information Fusion**, Amsterdam, v. 16, p. 59–67, Mar. 2014

HIKOSAKA, K.; HIROSE, T. Leaf angle as a strategy for light competition: optimal and evolutionarily stable light-extinction coefficient within a leaf canopy. **Ecoscience**, 1997.

HOMOLOVÁ, L.; MALENOVSKÝ, Z.; CLEVERS, J.G.P.W.; GARCÍA-SANTOS, G.; SCHAEPMAN, M.E. Review of optical-based remote sensing for plant trait mapping. **Ecological Complexity**, Amsterdam, v. 15, p. 1–16, Sept. 2013.

HOSOI, F.; NAKABAYASHI, K.; OMASA, K. 3-D modeling of tomato canopies using a high-resolution portable scanning lidar for extracting structural information. **Sensors**, Basel, v. 11, n. 2, p. 2166–74, Jan. 2011.

HOSOI, F.; NAKAI, Y.; OMASA, K. Estimating the leaf inclination angle distribution of the wheat canopy using a portable scanning lidar. **Journal of Agricultural Meteorology**, Amsterdam, v. 65, n. 3, p. 297–302, 2009.

HOUBORG, R.; BOEGH, E. Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data. **Remote Sensing of Environment**, New York, v. 112, n. 1, p. 186–202, 15 Jan. 2008.

HOUBORG, R.; SOEGAARD, H.; BOEGH, E. Combining vegetation index and model inversion methods for the extraction of key vegetation biophysical parameters using Terra and Aqua MODIS reflectance data. **Remote Sensing of Environment**, New York, v. 106, n. 1, p. 39–58, Jan. 2007.

HUANG, W.; NIU, Z.; WANG, J.A.; LIU, L.; ZHAO, C.; LIU, Q. Identifying crop leaf angle distribution based on two-temporal and bidirectional canopy reflectance. **IEEE Transactions on Geoscience and Remote Sensing**, New York, v. 44, n. 12, p. 3601–3609, Dec. 2006.

HUETE, A.R. A soil-adjusted vegetation index (SAVI). **Remote sensing of environment**, New York, v. 25, n. 3, p. 295–309, 1988.

HUTCHISON, B.A.; MATT, D.R.; MCMILLEN, R.T.; GROSS, L.J.; TAJCHMAN, S.J.; NORMAN, J.M. The Architecture of a Deciduous Forest Canopy in Eastern Tennessee, U.S.A. **Journal of Ecology**, New York, v. 74, n. 3, p. 635–646, 1986.

INDÚSTRIA BRASILEIRA DE ÁRVORES. **Relatório IBÁ**. Brasília, 2015.

JACQUEMOUD, S.; VERHOEF, W.; BARET, F.; BACOUR, C.; ZARCO-TEJADA, P.J.; ASNER, G.; FRANÇOIS, C.; USTIN, S.L. PROSPECT+SAIL models: a review of use for vegetation characterization. **Remote Sensing of Environment**, New York, v. 113, p. S56–S66, Sep. 2009.

JENSEN, J.R. **Introductory digital image processing: a remote sensing perspective.** Prentice Hall, 2005.

JONCKHEERE, I.; FLECK, S.; NACKAERTS, K.; MUYS, B.; COPPIN, P.; WEISS, M.; BARET, F. Review of methods for in situ leaf area index determination. **Agricultural and Forest Meteorology**, Amsterdam, v. 121, n. 1/2, p. 19–35, Jan. 2004.

KAMINSKI, T.; KNORR, W.; SCHOLZE, M.; GOBRON, N.; PINTY, B.; GIERING, R.; MATHIEU, P-P. Consistent assimilation of MERIS FAPAR and atmospheric CO₂ into a terrestrial vegetation model and interactive mission benefit analysis. **Biogeosciences**, Hoboken, v. 9, n. 8, p. 3173–3184, Aug. 2012.

KIMES, D.; GASTELLU-ETCHEGORRY, J-P.; ESTÈVE, P. Recovery of forest canopy characteristics through inversion of a complex 3D model. **Remote Sensing of Environment**, New York, v. 79, p. 320–328, 2002.

KIMES, D.S.; KNYAZIKHIN, Y.; PRIVETTE, J.L.; ABUEL GASIM, A.A.; GAO, F. Inversion methods for physically-based models. **Remote Sensing Reviews**, New York, v. 18, n. 2/4, p. 381–439, Sept. 2000.

KOBAYASHI, H.; SUZUKI, R.; KOBAYASHI, S. Reflectance seasonality and its relation to the canopy leaf area index in an eastern Siberian larch forest: Multi-satellite data and radiative transfer analyses. **Remote Sensing of Environment**, New York, v. 106, n. 2, p. 238–252, Jan. 2007.

KOETZ, B.; SCHAEPMAN, M.; MORSDORF, F.; BOWYER, P.; ITTEN, K.; LLGÖWER, B. Radiative transfer modeling within a heterogeneous canopy for estimation of forest fire fuel properties. **Remote Sensing of Environment**, New York, v. 92, n. 3, p. 332–344, Aug. 2004.

KOKALY, R.F.; ASNER, G.P.; OLLINGER, S.V.; MARTIN, M.E.; WESSMAN, C. Characterizing canopy biochemistry from imaging spectroscopy and its application to ecosystem studies. **Remote Sensing of Environment**, New York, v. 113, p. S78–S91, Sept. 2009.

KUCHARIK, C.J.M.; NORMAN, J.T.; GOWER, S. Measurements of leaf orientation, light distribution and sunlit leaf area in a boreal aspen forest. **Agricultural and Forest Meteorology**, Amsterdam, v. 91, n. 1;2, p. 127–148, May 1998.

KUUSK, A. A fast invertible canopy reflectance model. **Remote Sensing of Environment**, Amsterdam, v. 350, p. 342–350, May 1995.

KUUSK, A.; NILSON, T.A. Directional multispectral forest reflectance model. **Remote Sensing of Environment**, New York, v. 252, p. 244–252, 2000.

LACLAU, J-P.; GONÇALVES, J.L.D.M.; STAPE, J.L. Perspectives for the management of *Eucalypt* plantations under biotic and abiotic stresses. **Forest Ecology and Management**, Amsterdam, v. 301, p. 1–5, Aug. 2013.

LANG, A.R.G. Application of some of Cauchy's theorems to estimation of surface areas of leaves, needles and branches of plants, and light transmittance. **Agricultural and Forest Meteorology**, Amsterdam, v. 55, n. 3/4, p. 191–212, June 1991.

LANG, A.R.G.; XIANG, Y.Q.; NORMAN, J.M. Crop structure and the penetration of direct sunlight. **Agricultural and Forest Meteorology**, Amsterdam, v. 35, p. 83–101, 1985.

LAURENT, V.C.E.; VERHOEF, W.; CLEVERS, J.G.P.W.; SCHAEPMAN, M.E. Estimating forest variables from top-of-atmosphere radiance satellite measurements using coupled radiative transfer models. **Remote Sensing of Environment**, New York, v. 115, n. 4, p. 1043–1052, Apr. 2011a.

LAURENT, V.C.E.; VERHOEF, W.C.; JAN G.P.W.; SCHAEPMAN, M.E. Inversion of a coupled canopy–atmosphere model using multi-angular top-of-atmosphere radiance data: A forest case study. **Remote Sensing of Environment**, New York, v. 115, n. 10, p. 2603–2612, Oct. 2011b.

le MAIRE, G.; MARSDEN, C.; NOUVELLON, Y.; STAPE, J.L.; PONZONI, F. Calibration of a Species-Specific Spectral Vegetation Index for Leaf Area Index (LAI) monitoring: example with MODIS reflectance time-series on *Eucalyptus* plantations. **Remote Sensing**, Lower Hutt, v. 4, n. 12, p. 3766–3780, Nov. 2012.

le MAIRE, G.; MARSDEN, C.; NOUVELLON, Y.; GRINAND, C.; HAKAMADA, R.; STAPE, J.L.; LACLAU, J-P. MODIS NDVI time-series allow the monitoring of Eucalyptus plantation biomass. **Remote Sensing of Environment**, New York, v. 115, n. 10, p. 2613–2625, Oct. 2011a.

le MAIRE, G.; MARSDEN, C.; VERHOEF, W.; PONZONI, F.J.; LO SEEN, D.; BÉGUÉ, A.; STAPE, J.L.; NOUVELLON, Y. Leaf area index estimation with MODIS reflectance time series and model inversion during full rotations of *Eucalyptus* plantations. **Remote Sensing of Environment**, New York, v. 115, n. 2, p. 586–599, Feb. 2011b.

le MAIRE, G.; FRANCOIS, C.; SOUDANI, K.; BERVEILLER, D.; PONTAILLER, J.; BRÉDA, N.; GENET, H.; DAVI, H.; DUFRÊNE, E. Calibration and validation of hyperspectral indices for the estimation of broadleaved forest leaf chlorophyll content, leaf mass per area, leaf area index and leaf canopy biomass. **Remote Sensing of Environment**, New York, v. 112, n. 10, p. 3846–3864, Oct. 2008.

LEMOS, C.C.Z. **Aprimoramentos, teste e uso do modelo 3-PG em plantios clonais de Eucalyptus no nordeste do estado de São Paulo**. 2012. 171 p. Tese (Doutorado em Recursos Florestais) - Escola Superior de Agricultura “Luiz de Queiroz”, Universidade de São Paulo, Piracicaba, 2012.

LIANG, L.; DI, L.; ZHANG, L.; DENG, M.; QIN, Z.; ZHAO, S.; LIN, H. Estimation of crop LAI using hyperspectral vegetation indices and a hybrid inversion method. **Remote Sensing of Environment**, New York, v. 165, p. 123–134, Aug. 2015.

LIANG, S.; ZHONG, B.; FANG, H. Improved estimation of aerosol optical depth from MODIS imagery over land surfaces. **Remote Sensing of Environment**, New York, v. 104, n. 4, p. 416–425, Oct. 2006.

MA, H.; SONG, J.; WANG, J.; XIAO, Z.; FU, Z. Improvement of spatially continuous forest LAI retrieval by integration of discrete airborne LiDAR and remote sensing multi-angle optical data. **Agricultural and Forest Meteorology**, Amsterdam, v. 189/190, p. 60–70, June 2014.

MALENOVSKÝ, Z.; HOMOLOVÁ, L.; ZURITA-MILLA, R.; SCHAEPMAN, M.E.; CLEVERS, J.G.P.W.; MARTIN, E.; GASTELLU-ETCHEGORRY, J-P. Physically-based retrievals of Norway spruce canopy variables from very high spatial resolution hyperspectral data. In: INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMPOSIUM, 2007. **Proceedings...** p. 4057–4060.

MALENOVSKÝ, Z.; HOMOLOVÁ, L.; ZURITA-MILLA, R.; LUKEŠ, P.; KAPLAN, V.; HANUŠ, J.; GASTELLU-ETCHEGORRY, J-P.; SCHAEPMAN, M.E. Retrieval of spruce leaf chlorophyll content from airborne image data using continuum removal and radiative transfer. **Remote Sensing of Environment**, New York, v. 131, p. 85–102, Apr. 2013.

MALENOVSKY, Z.; MARTIN, E.; HOMOLOVA, L.; GASTELLU-ETCHEGORRY, J.P.; ZURITAMILLA, R.; SCHAEPMAN, M.; POKORNY, R.; CLEVERS, J.; CUDLIN, P. Influence of woody elements of a Norway spruce canopy on nadir reflectance simulated by the DART model at very high spatial resolution. **Remote Sensing of Environment**, New York, v. 112, n. 1, p. 1–18, Jan. 2008.

MARSDEN, C.; LE MAIRE, G.; STAPE, J. L.; SEEN, D.L.; ROUPSARD, O.; CABRAL, O.; EPRON, D.; LIMA, NASCIMENTO, A. M.; NOUVELLON, Y. Relating MODIS vegetation index time-series with structure, light absorption and stem production of fast-growing Eucalyptus plantations. **Forest Ecology and Management**, Amsterdam, v. 259, n. 9, p. 1741–1753, Apr. 2010.

MARSDEN, C.; NOUVELLON, Y.; LACLAU, J-P.; CORBEELS, M.; MCMURTRIE, R.E.; STAPE, J.L.; EPRON, D.; LE MAIRE, G. Modifying the G'DAY process-based model to simulate the spatial variability of Eucalyptus plantation growth on deep tropical soils. **Forest Ecology and Management**, Amsterdam, Nov. 2012.

MCCALLUM, I.; WAGNER, W.; SCHMULLIUS, C.; SHVIDENKO, A.; OBERSTEINER, A.; FRITZ, S.; NILSSON, S. Comparison of four global FAPAR datasets over Northern Eurasia for the year 2000. **Remote Sensing of Environment**, New York, v. 114, n. 5, p. 941–949, maio 2010.

MEDLYN, B.E. MAESTRO_Retrospective (Medlyn, 2004). In: MENCUCCINI, M. et al. (Eds.). **Forests at the Land-Atmosphere Interface**. Wallingford, UK: CABI, 2004. p. 105–122.

MYNENI, R.B. Estimation of global leaf area index and absorbed par using radiative transfer models. **IEEE Transactions on Geoscience and Remote Sensing**, New York, v. 35, n. 6, p. 1380–1393, 1997.

NOGUEIRA, R.I. **Caracterização anatômica foliar de 16 genótipos de Eucalyptus de alta produtividade do Brasil**. 2014. 114 p. Dissertação (Mestrado em Engenharia Florestal) - Faculdade de Ciências Agrônômicas, Universidade Estadual Paulista “Júlio de Mesquita Filho”, Botucatu, 2014.

NORTH, P.R.J. Estimation of f APAR , LAI , and vegetation fractional cover from ATSR-2 imagery. **Remote Sensing of Environment**, New York, v. 80, p. 114–121, 2002.

OLLINGER, S.V. Sources of variability in canopy reflectance and the convergent properties of plants. **New phytologist**, Cambridge, v. 189, n. 2, p. 375–94, Jan. 2011.

PICKETT-HEAPS, C.A.; CANADELL, J.G.; BRIGGS, P.R.; GOBRON, N.; HAVERD, V.; PAGET, M.J.; PINTY, B.; RAUPACH, M.R. Evaluation of six satellite-derived Fraction of Absorbed Photosynthetic Active Radiation (FAPAR) products across the Australian continent. **Remote Sensing of Environment**, New York, v. 140, p. 241–256, Jan. 2014.

PINTY, B.; LAVERGNE, T.; DICKINSON, R.E.; WIDLowski, J-L.; GOBRON, N.; VERSTRAETE, M.M. Simplifying the interaction of land surfaces with radiation for relating remote sensing products to climate models. **Journal of Geophysical Research: Atmospheres**, Hoboken, v. 111, n. D2, p. D02116, Jan. 2006.

PISEK, J.; RYU, Y.; ALIKAS, K. Estimating leaf inclination and G-function from leveled digital camera photography in broadleaf canopies. **Trees**, Berlin, v. 25, n. 5, p. 919–924, Apr. 2011.

PONZONI, F.J.; SHIMABUKURO, Y.E. **Sensoriamento remoto no estudo da vegetação**. São José dos Campos: INPE, 2007.

PROPASTIN, P.A. Spatial non-stationarity and scale-dependency of prediction accuracy in the remote estimation of LAI over a tropical rainforest in Sulawesi, Indonesia. **Remote Sensing of Environment**, New York, v. 113, n. 10, p. 2234–2242, Oct. 2009.

ROBERTS, J.W.; TESFAMICHAEL, S.; GEBRESLASIE, M.; AARDT, J.V.; AHMED, F.B. Forest structural assessment using remote sensing technologies : an overview of the current state of the art. **Southern Hemisphere Forestry Journal**, Rotorua, v. 69, n. 3, p. 183–203, 2007.

ROGERS, N.S. **Estimation of Leaf Area Index and simulation of evapotranspiration in intensively managed douglas-fir forests**. 2013. Thesis - Department of Forest Engineering, Resources & Management, Oregon State University, 2013.

RONDEAUX, G.; STEVEN, M.; BARET, F. Optimization of soil-adjusted vegetation indices. **Remote Sensing of Environment**, New York, v. 55, n. 2, p. 95–107, 1996.

ROSS, J.K. **The radiation regime and architecture of plant stands**. Dr. W. Junk Publ., 1981.

ROUSE, J.W.; HAAS, R.H.; SCHELL, J.A.; DEERING, D.W. Monitoring vegetation systems in the Great Plains with ERTS. NASA Goddard Space Flight Center 3d ERTS-1 Symposium. **Proceedings...** United States: 1973.

RUNNING, S.W.; PETERSON, D.L.; SPANNER, M.A.; TEUBER, K.B. Remote sensing of coniferous leaf area. **Ecology**, Brooklyn, v. 67, n. 1, p. 273–276, 1986.

SCHLERF, M.; ATZBERGER, C.; HILL, J.; BUDDENBAUM, H.; WERNER, W.; SCHÜLER, G. Retrieval of chlorophyll and nitrogen in Norway spruce (*Picea abies* L. Karst.) using imaging spectroscopy. **International Journal of Applied Earth Observation and Geoinformation**, Enschede, v. 12, n. 1, p. 17–26, Feb. 2010.

SCHLERF, M.; ATZBERGER, C.; HILL, J. Remote sensing of forest biophysical variables using HyMap imaging spectrometer data. **Remote Sensing of Environment**, New York, v. 95, n. 2, p. 177–194, Mar. 2005.

SEIXAS, J.; CARVALHAIS, N.; NUNES, C.; BENALI, A. Comparative analysis of MODIS-FAPAR and MERIS-MGVI datasets: Potential impacts on ecosystem modeling. **Remote Sensing of Environment**, New York, v. 113, n. 12, p. 2547–2559, Dec. 2009.

SENNA, M.C.A.; COSTA, M.H.; SHIMABUKURO, Y.E. Fraction of photosynthetically active radiation absorbed by Amazon tropical forest: a comparison of field measurements, modeling, and remote sensing. **Journal of Geophysical Research**, Washington, v. 110, 2005.

SINOQUET, H.; THANISAWANYANGKURA, S.; MABROUK, H.; KASEMSAP, P. Characterization of the light environment in canopies using 3D digitising and image processing. **Annals of Botany**, Oxford, p. 203–212, 1998.

SINOQUET, H.; SONOHAT, G.; PHATTARALERPHONG, J.; GODIN, C. Foliage randomness and light interception in 3-D digitized trees : an analysis from multiscale discretization of the canopy. **Plant, Cell and Environment**, Oxford, v. 28, p. 1158–1170, 2005.

SMITH, M.-L.; OLLINGER, S.V.; MARTIN, M.E.; ABER, J.D.; HALLETT, R.A.; GOODALE, C.L. Direct estimation of aboveground forest productivity through hyperspectral remote sensing of canopy nitrogen. **Ecological Applications**, Tempe, v. 12, n. 5, p. 1286–1302, 2002.

SMITH, W.K.; SCHOETTLE, A.W.; CUI, M. Importance of the method of leaf area measurement to the interpretation of gas exchange of complex shoots. **Tree Physiology**, Oxford, v. 8, n. 2, p. 121–127, Mar. 1991.

STENBERG, P. Simulations of the effects of shoot structure and orientation on vertical gradients in intercepted light by conifer canopies. **Tree Physiology**, Oxford, v. 16, n. 1/2, p. 99–108, 1996.

THANISAWANYANGKURA, S.; SINOQUET, H.; RIVET, P.; CRETENET, M.; JALLAS, E. Leaf orientation and sunlit leaf area distribution in cotton. **Agricultural and Forest Meteorology**, Amsterdam, v. 86, n. 1/2, p. 1–15, Aug. 1997.

THOMAS, S.C.; WINNER, W.E. A rotated ellipsoidal angle density function improves estimation of foliage inclination distributions in forest canopies. **Agricultural and Forest Meteorology**, Amsterdam, v. 100, n. 1, p. 19–24, Jan. 2000.

TROMBETTI, M.; RIANO, D.; RUBIO, M.; CHENG, Y.; USTIN, S. Multi-temporal vegetation canopy water content retrieval and interpretation using artificial neural networks for the continental USA. **Remote Sensing of Environment**, New York, v. 112, n. 1, p. 203–215, Jan. 2008.

VERHOEF, W. **Theory of radiative transfer models applied in optical remote sensing of vegetation canopies**. Wageningen: Landbouwniversiteit Wageningen, 1998.

VERSTRAETE, M.M.; GOBRON, N.; AUSSDAT, O.; ROBUSTELLI, M.; PINTY, B.; WIDLOWSKI, J-L.; TABERNER, M. An automatic procedure to identify key vegetation phenology events using the JRC-FAPAR products. **Advances in Space Research**, Oxford, v. 41, n. 11, p. 1773–1783, Jan. 2008.

WANG, Q.; ADIKU, S.; TENHUNEN, J.; GRANIER, A. On the relationship of NDVI with leaf area index in a deciduous forest site. **Remote Sensing of Environment**, New York, v. 94, n. 2, p. 244–255, Jan. 2005.

WANG, W.M.; LI, Z.L.; SU, H.B. Comparison of leaf angle distribution functions: effects on extinction coefficient and fraction of sunlit foliage. **Agricultural and Forest Meteorology**, Amsterdam, v. 143, n. 1-2, p. 106–122, Mar. 2007.

WANG, Z.; LIU, C.; HUETE, A. From AVHRR-NDVI to MODIS-EVI: Advances in vegetation index research. **Acta Ecologica Sinica**, Amsterdam, v. 23, n. 5, p. 979–987, 2002.

WATSON, D.J. Comparative physiological studies on the growth of field crops: i. Variation in net assimilation rate and leaf area between species and varieties, and within and between years. **Annals of Botany**, Oxford, v. 11, n. 1, p. 41–76, Jan. 1947.

WEISS, M.; BARET, F.; SMITH, G.J.; JONCKHEERE, I.; COPPIN, P. Review of methods for in situ leaf area index (LAI) determination. **Agricultural and Forest Meteorology**, Amsterdam, v. 121, n. 1/2, p. 37–53, Jan. 2004.

WIRTH, R.; WEBER, B.; RYEL, R. J. Spatial and temporal variability of canopy structure in a tropical moist forest. **Acta Oecologica**, Paris, v. 22, n. 5/6, p. 235–244, Sept. 2001.

WU, C.; NIU, Z.; GAO, S. The potential of the satellite derived green chlorophyll index for estimating midday light use efficiency in maize, coniferous forest and grassland. **Ecological Indicators**, Amsterdam, v. 14, n. 1, p. 66–73, Mar. 2012.

ZHANG, Q.; MIDDLETON, E.M.; MARGOLIS, H.; DROLET, G.G.; BARR, A.; BLACK, T. A. Can a satellite-derived estimate of the fraction of PAR absorbed by chlorophyll (FAPARchl) improve predictions of light-use efficiency and ecosystem photosynthesis for a boreal aspen forest? **Remote Sensing of Environment**, New York, v. 113, n. 4, p. 880–888, 2009.

ZHAO, D.; HUANG, L.; LI, J.; QI, J. A comparative analysis of broadband and narrowband derived vegetation indices in predicting LAI and CCD of a cotton canopy. **ISPRS Journal of Photogrammetry and Remote Sensing**, Amsterdam, v. 62, n. 1, p. 25–33, May 2007.

ZHAO, F.; YANG, X.; SCHULL, M.A.; ROMÁN-COLÓN, M.O.; YAO, TIAN; WANG, Z.; ZHANG, Q.; JUPP, D.L.B.; LOVELL, J.L.; CULVENOR, D.S.; NEWNHAM, G.J.; RICHARDSON, A.D.; NI-MEISTER, W.; SCHAAF, C.L.; WOODCOCK, C.E.; STRAHLER, A.H. Measuring effective leaf area index, foliage profile, and stand height in New England forest stands using a full-waveform ground-based lidar. **Remote Sensing of Environment**, New York, v. 115, p. 2954–2964, 2011.

ZHENG, G.; MOSKAL, L.M. Retrieving leaf area index (LAI) using remote sensing: theories, methods and sensors. **Sensors**, Basel, v. 9, n. 4, p. 2719–2745, Jan. 2009.

ZOU, X.; MÖTTUS, M.; TAMMEORG, P.; TORRES, C.L.; TAKALA, T.; PISEK, J.; MÄKELÄ, P.; STODDARD, F.L.; PELLIKKA, PETRI. Photographic measurement of leaf angles in field crops. **Agricultural and Forest Meteorology**, Amsterdam, v. 184, p. 137–146, Jan. 2014.

2 ACCURACY OF THE DART MODEL TO SIMULATE VERY HIGH SPATIAL RESOLUTION SATELLITE IMAGES OF *EUCALYPTUS* STANDS OF DIFFERENT AGES AND GENOTYPES

Abstract

In this study, we parameterize and validate the DART radiative transfer model using extensive *in situ* measurements as input. *Eucalyptus* plantations from 16 different genotypes were simulated. Accuracy of the simulations of stand reflectance was achieved by comparing the simulation with very high-resolution satellite images at three different ages. The study site was located in Itatinga Municipality, in the state of São Paulo, southeastern Brazil, where two different experiments were analyzed: the first experiment consisted of 4 plots of 84 trees each chosen within an industrial stand, in real planting conditions. The second experiment consisted of a “clonal test”, where plots of 100 trees of 16 different genotypes were planted in 10 randomized blocks, totalizing 16,000 trees. Regular inventories were conducted for the first experiment, at 3, 5, 6, 9, 12, 15, 18, 21, 25, 31, 39, 44, 51 and 57 months after planting. For the second experiment, inventories were conducted at 6, 12, 19, 26, 38, 52, 62 months. Leaves, soil and trunk spectral optical properties were collected in 2010 and 2015, and SPAD measurements (highly correlated with chlorophyll content) were collected in 2010 and 2014. The DART model was parameterized using measured tree dimensions interpolated in the 3 dates of satellite measurements from field measurements. The DART model was run with the atmospheric module, which allowed simulating images at bottom and top of atmosphere (BOA and TOA) in the three dates of satellite measurements (May 2010, August 2010 and July 2013), when the stand was 6, 9 and 44 months of age, respectively. Accuracy of the simulations was evaluated by comparing the mean TOA reflectance of DART with mean reflectance (TOA) measured by the Worldview-2 in the three dates. The mean absolute error (MAE) was computed for eight multispectral bands in the three dates. The multispectral reflectance of genotypes in all ages at BOA level was also analyzed for DART and Worldview-2 images. Results showed a good simulation of the spectra, with MAE lower than 0.045 for all bands. DART was very accurate to simulate reflectance of bands in the visible region (MAE < 0.016). However, some limitations were found in the simulations of bands in the near infrared band (NIR1 band - 770-785 nm), mainly at 44 months of age. These results could be associated with limitations in the model to simulate the shadow effect. Despite these limitations, this systematic error in the near infrared bands does not make DART usage impossible, since post-processing techniques could be implemented to correct the simulation based on measurements. Similar reflectance hierarchy between genotypes for DART and Worldview-2 multispectral bottom of atmosphere (BOA) level reinforces DART suitability to describe the radiative transfer on forest landscapes at different ages. The more pronounced effect of genotypes in the NIR bands suggests that the structural variability of the stand was the main factor to show these differences and, not necessarily, the chlorophyll content. Higher reflectance in the near infrared region at BOA level for the genotypes with higher leaf areas at the specific date reinforces the impact of this parameter in the canopy reflectance of the *eucalyptus* stands. This study shows the potential of DART to simulate reflectance spectra of *Eucalyptus* stands at different ages and open perspectives on its use in inversion mode.

Keywords: *Eucalyptus* plantations; Clonal plantations; Remote sensing; 3D radiative transfer model

2.1 Introduction

Commercial *Eucalyptus* plantations in Brazil cover 5.6 million ha, which accounts for 71.9 % of planted forests in Brazil (IBÁ, 2015). Currently, most areas are planted with a few *Eucalyptus* species, but a large variety of genotypes, planted mainly on clonal plantations, which were tested and selected for distinct widespread soils and climatic Brazilian conditions (STAPE et al., 2014). These genotypes provide different phenotypes, with distinct canopy structure, leaf morphology and biochemical compounds, allocation patterns and growth speed and, consequently, different biomass production. Due to their high economic importance in Brazil, the understanding of how biophysical parameters of planted forests could explain the spatial-temporal growth dynamics is of paramount importance. These biophysical parameters are also needed to address the use of resources and ecological functioning of these plantations.

Among the several methods to characterize biophysical parameters of forest plantations, the development of remote sensing applications has become one feasible and robust technique, since these applications are able to express - through light interaction between earth-atmosphere compounds - canopy variables of forest ecosystems over several temporal and spatial scales. Remotely sensed images, in particular those obtained from orbital platforms, can be converted into reflectance values for each spectral band of the image, and later used to retrieve biophysical parameters of the forest through empirical relationships, or through radiative transfer models (RTM). This last method, despite being more complex, is based on a better understanding of the physical laws that control the transfer and the interaction of solar radiation in a vegetative canopy to explain the quantitative values of canopy reflectance (GASTELLU-ETCHEGORRY; BRUNIQUEL-PINEL, 2001). This physically-based approach is better suited for large-scale applications (GOBRON et al., 1997; VERSTRAETE et al., 2008) and can also make full use of the high dimensional spectral and multi-angular information provided by many modern sensors (BANSKOTA et al., 2015; CHOPPING et al., 2008; DARVISHZADEH et al., 2008b).

Applications with physically-based RTM have become a reliable alternative to describe vegetation functioning, mainly through the use of three dimensional (3D) models, which are able to simulate accurately the spectral behavior of bi-directional reflectance factor (BRDF) of the Earth's surfaces (GASTELLU-ETCHEGORRY et al., 2004). The expected advantage of these 3D RTM is to provide an accurate 3D distribution of the radiation that is intercepted and absorbed by natural vegetation (GASTELLU-ETCHEGORRY, 2008), as well as a better simulation of the light reflected toward the atmosphere and measured by satellites, especially in heterogeneous canopies.

In this context, the DART - Discrete Anisotropic Radiative Transfer - model (GASTELLU-ETCHEGORRY et al., 1996) is a comprehensive 3D RTM model, simulating BRDFs, remote sensing images and the spectral radiation budget of 3D natural landscapes in the visible and near infrared domain. This model enables new possibilities of data evaluation, especially using very high resolution images, field measured parameters and optical properties of landscape components to evaluate, for example, the canopy structure on satellite image texture (GASTELLU-ETCHEGORRY; BRUNIQUEL-PINEL, 2001), surface radiative budget (BANSKOTA et al., 2015; CARRER et al., 2013; GASTELLU-ETCHEGORRY; TRICHON, 1998; GASTELLU-ETCHEGORRY, 2008), photosynthesis and primary production rates of vegetation canopies (GUILLEVIC, 1999; ZHANG et al., 2009) and forest LAI estimation (BANSKOTA et al., 2015), among others. At this level of analysis, local variability such as ground surface characteristics, tree sizes and sun illumination geometry are significant issues within the model.

Despite the successful use of the physical approach of DART to retrieve canopy characteristics from simulations of remote sensing data, the need of specific field measurements and local conditions to calibrate the model requires evaluation of its sensitivity to assess reflectance similar to that obtained from real acquired sensor images to verify the model reliability to estimate biophysical parameters of heterogeneous forest stands. This validation of the DART RTM in forward mode is necessary to decide whether DART can simulate *Eucalyptus* plantations reflectance in the visible and near infrared domain. In this study, we addressed the goal to parameterize the DART model using an extensive *in situ* measurement dataset as input. *Eucalyptus* plantations of 16 different genotypes and three different ages were used to verify the DART accuracy comparing with real satellite images obtained from very high resolution.

2.2 Material and Methods

2.2.1 Study Site

The study site was located in Itatinga Municipality, in the state of São Paulo, southeastern Brazil, 22°58'04''S and 48°43'40''W. In the last 15 years, average annual rainfall was about 1391 mm, with 75% of this total concentrated between October and March (CAMPOE et al., 2013). Average annual temperature from January 2010 to December 2012 was 19.3°C, ranging from 16.3°C (June to August) to 22.2°C (December to February). The average annual relative humidity was 75%, with minimum values observed between June and September ($\approx$ 30%). The slope was lower than 5% and the maximum area elevation was

760 m above sea level (DA SILVA et al., 2011). Soils are very deep oxisols in the upper part of the study site (750 m above sea level) with low clay content ($\approx 20\%$) and at the lowest elevation (725 m above sea level) with high clay content ($\approx 40\%$).

A stand of 200 ha was planted in November 2009 with a commercial clone of *Eucalyptus grandis* (W. Hill ex Maiden). Within this area, at the same planting date, a “clonal test” was installed with 16 different genotypes (treatments) comprising several genetic origins from different enterprises and regions in Brazil (Table 1); 14 of these genotypes were clones and two had seminal origin. The clone planted in treatment 3 of the clonal test was the same as the one planted in 200 ha of the main stand. The clonal test experiment was designed to evaluate genetic variability effect on productivity of currently cultivated genotypes (IPEF, 2012).

Table 1 - Description of the 16 treatments (genotypes) used in the clonal test

Treatment	Description	Name
1	<i>E. grandis</i> seeds CH Duratex	SEM01
2	<i>E. grandis</i> seeds monoprogeny Duratex	MON02
3	<i>E. grandis</i> Clone Eucflux	EUC03
4	<i>E. grandis x urophylla</i> Clone Duratex	DUR04
5	<i>E. grandis x urophylla</i> Clone Fibria	FIB05
6	<i>E. grandis x urophylla</i> Clone Fibria	FIB06
7	<i>E. grandis x urophylla</i> Clone V&M Tubes	VMT07
8	<i>E. grandis x urophylla</i> Clone Cenibra	CEN08
9	<i>E. grandis x urophylla</i> Clone Copener - Humid area	COP09
10	<i>E. grandis</i> Clone Conpacel	CON10
11	<i>E. grandis x urophylla</i> Clone Suzano - High productivity	SUZ11
12	<i>E. grandis x urophylla</i> Clone ArcelorMittal BioEnergia	AMB12
13	<i>E. grandis x urophylla</i> Clone ArcelorMittal BioEnergia	AMB13
14	<i>E. saligna</i> Clone Klabin	KLA14
15	<i>E. grandis x urophylla</i> Clone Suzano - Medium productivity	SUZ15
16	<i>E. camaldulensis x grandis</i> Clone Copener - Dry area	COP16

Planting lines of the clonal test were mainly east-west oriented, with plant arrangement of 3.75 m $\times$ 1.60 m (1666 trees per hectare). The clonal test area comprised 10 blocks, each having 16 treatments randomly distributed within a 4 x 4 subplot grid (Figure 1). Each treatment (genotype) included 12 rows of 16 trees (3 x 2 m), totaling 192 trees per plot. In this case, we analyzed only 100 trees located in the central part of the plot and the other trees were considered as border. Four plots in the main stand area (*E. grandis* stand, 200 ha) were analyzed, each having six rows and 14 trees per row (3.75 m $\times$ 1.60 m), totaling 84 trees per plot. Figure 2 shows the location of the plots and clonal test blocks.

Figure 1 - Representation of one block for clonal test. Each color is a different treatment (genotype, labeled G1 to G16 representing each of the 16 treatments). Circles represent the crown size. Red stars are LAI measurement positions (measured with LAI-2000 equipment, not used in this study). Surrounding trees were considered as border trees. Author: Guerric le Maire (not published yet)

In the whole area, standard silvicultural practices were conducted, including glyphosate to eliminate weed competition before site preparation and until canopy closure (≈ 18 months after planting); ant control (*Atta* sp. e *Acromyrmex* sp.) with sulfluramid was carried out when needed; fertilization (see the detailed description in Campoe et al. (2012)).

Figure 2 - Location of study site. Hollow rectangles are representative of *E. grandis* stand plots and filled rectangles area representative of the blocks in the clonal test. The arrow indicates the trend of increase in soil clay content from ≈ 20 to $\approx 40\%$ across the site

2.2.2 *In-situ* measurements

Complete forest inventories were conducted at 3, 5, 6, 9, 12, 15, 18, 21, 25, 31, 39, 44, 51 and 57 months after planting for Plots 1 to Plot 4, and at 6, 12, 19, 26, 38, 52, 62 months for the clonal test. During these inventories, crown circumference and tree height were measured at age < 18 months, and after this age, only trunk circumference at breast height (CBH) was measured, with occasional measurements of tree height. In each of these dates, 12

trees of different sizes were cut for the *Eucalyptus grandis* stand around plot 1 to plot 4, and 10-12 trees were cut for each genotype in the clonal test (trees selected within different blocks), within the border trees. These destructive measurements were used to calibrate allometric relationships between trunk CBH and tree height, between CBH and canopy height, CBH and crown diameter in the planting line and inter-rows directions, CBH and tree total leaf area, CBH and biomass of different tree components (leaves, branches, bark and stem wood).

Leaf angle distribution (LAD) was computed from the leaf angles orientation measured in the field in six felled trees for each genotype. In each tree, the inclination of 72 leaves was measured with a clinometer. These 72 leaves were selected according to their position within the crown: three different crown heights (bottom, middle and top layers), four auxiliary branches at each height (two in row planting and two in inter-row planting), and six leaves along the length of these auxiliary branches.

The tree leaf area was determined for each tree using allometric relationships calibrated on 10 felled trees. Leaf area of young trees was calculated using the power equation 1.

$$LA = \alpha(CH)^\beta \quad (1)$$

Where: LA = tree total leaf area (m²); C = crown radius (m); H = tree height (m); α, β = equation parameters.

For the other ages, equation 2 was used (LACLAU et al., 2008):

$$LA = \alpha(D^2H)^\beta \quad (2)$$

Where: LA = leaf area (m²); D = trunk diameter (m); H = tree height (m); α, β = equation parameters.

The main characteristics of the plots during the years of analysis in the *E. grandis* stand and clonal test are shown, respectively, in Table 2 and Figure 3. These data were extracted by interpolation of the field measurements data in the three dates that were analyzed in this study. For the leaf area, additional estimations were extracted using auxiliary leaf area index values retrieved from MODIS images during the months after planting.

Table 2 - Trees characteristics of *Eucalyptus grandis* stand per date of acquired satellite images

Date	Age ¹ (months)	Stems ¹	Height ¹ (m)	DBH ^{1,2} (cm)	Crown diameter ¹ (m)	Leaf area ¹ (m ²)
May,2010	6	82.7 (0.5)	2.41 (0.73)	2.06 (0.7)	1.44 (0.38)	5.99 (2.51)
Aug,2010	9	82.7 (0.5)	3.59 (0.98)	3.00 (0.89)	1.86 (0.38)	9.93 (4.84)
July,2013	44	81.7 (1.5)	18.90 (5.39)	12.06 (3.69)	2.57 (0.72)	19.53 (7.72)

¹Average values (standard deviation). ²Diameters at breast height.

Figure 3 - Average values of the trees characteristics of clonal test of each treatment (genotypes, labeled G1 to G16) at 6, 9 and 44 months of age (on May 2010, Aug 2010 and July 2013, respectively). (a) Diameter at Breast Height -DBH (cm), (b) total tree height (m), (c) crown diameter (m), (d) number of stems and (e) leaf area (m²)

Leaves, trunk and litter optical properties were measured with ASD Field SpecPro (Analytical Spectral Devices, Boulder, Colorado, USA) spectrometer in the spectral range from 300 to 2500 nm at 12 and 71 months after planting, respectively, in November 2010 and October 2015. Leaf optical properties comprehended the reflectance and transmittance collected using LiCor integrating sphere. In these dates, three trees per treatment (genotypes) were selected and for each tree, leaves were collected at three crown layers (bottom, middle and top) and two horizontal positions in each layer, totaling two leaves per crown layer, six leaves per tree and 18 leaves per treatment. Litter and trunk optical properties comprehended

the reflectance. In November 2010, litter and trunk reflectance were collected only for the *Eucalyptus grandis* stand directly in the field. On October 2015, litter and trunk reflectance were collected for each treatment (genotypes) in three different locations in the field in order to generate one composite sample per treatment and measured in the laboratory using a Contact Probe in five different points of the composite sample.

Additionally, chlorophyll content of leaves for the clonal test was estimated with the SPAD device (Minolta Inc.) in November 2010 and May 2014, when plants were at 12 and 48 months of age, respectively. As for spectral measurements, three trees per treatment (genotypes) were selected and SPAD values of six leaves per tree were recorded.

2.2.3 The 3D DART radiative transfer model

The Discrete Anisotropic Radiative Transfer (DART) is a comprehensive model and can be used to retrieve physically based canopy parameter. DART simulates radiative transfer in heterogeneous 3D landscapes with the exact kernel and discrete ordinate methods (GASTELLU-ETCHEGORRY et al., 2004). Any landscape is simulated as a rectangular matrix of parallelepiped cells that contains turbid material and/or planar elements. Radiation propagates in a finite number of directions with an angular sector width (steradian). Incident Irradiance on the scene has the direct sun and atmospheric (diffuse) source vectors. They are assumed to originate from a fictitious cell layer at the top of the scene and the atmospheric source vectors implies the use of a coupled atmospheric mode. More detailed information on DART physical components can be found in CESBIO (2013a, 2013b, 2013c) and GASTELLU-ETCHEGORRY et al. (2004).

DART uses information from spectral intervals - or spectral bands - with mean optical properties of the simulated objects. Output options include computation of images with bidirectional reflectance at the bottom and top of atmosphere in several sensor acquisition and sun illumination geometries, radiative budget products, land cover maps, among others.

Simulations of vegetation landscapes require, besides the definition of the spectral bands and their computation methods, input parameters related to the structural characteristics of trees (e.g. tree position and dimensions, leaf area index and leaf angle distribution), the optical properties of scene compounds, sun position, view angle, position and structural characteristics of the objects, scene dimensions and cell size.

2.2.4 DART parameterization

2.2.4.1 Spectral intervals

In DART parameterization, we used the "ray tracing" and R (reflectance) mode for the simulation method in order to allow the simulation of bidirectional reflectance images of 21 spectral intervals (bands). These bands were defined to cover the main region of canopy reflectance analysis, mainly in the visible and infrared spectrum, from 360 to 1100 nm with width ranging from 20 , 30 and 40 nm (band 1= 380-420 nm, band 2= 420-460 nm, band 3= 460-500 nm, band 4= 500-540 nm, band 5= 540-580 nm, band 6= 580-620 nm, band 7= 620-660 nm, band 8= 660-690 nm, band 9= 690-710 nm, band 10= 710-730 nm, band 11= 730-750 nm, band 12= 750-780 nm, band 13= 780-810 nm, band 14= 810-840 nm, band 15= 840-880 nm, band 16= 880-920 nm, band 17= 920-960 nm, band 18= 960-1000 nm, band 19= 1000-1040 nm, band 20= 1040-1080 nm and band 21= 1080-1100 nm). The spectral intervals with smaller amplitudes were used for the spectral bands that normally show large canopy reflectance variability in small wavelength regions, such as the red and red edge bands (≈ 625 to 740 nm). In these regions, the leaf reflectance curve increases until reaching a plateau in the infrared region (Figure 4 in Section 1.3 of Chapter 1). From these 21 bands, it was possible to reconstruct a full reflectance spectrum by interpolating the images from each band. Afterward, these bands were convolved for broadband areas corresponding to multispectral bands of satellite sensors using their relative spectral response.

2.2.4.2 Illumination parameters

Simulation of virtual eucalyptus plantation forests was run based on 100 discrete illumination directions, which correspond to the solid angle between the beam emitted by solar source and atmosphere surface. The number of direction was chosen to maintain the accuracy while reducing the processing time. The input solar zenith and azimuth angles (respectively, θ_s and ϕ_s) were computed knowing the exact local latitude ($22^\circ 58' 04''$ S) and date and hour of satellite overpass. Image acquisition geometry (θ_v, ϕ_v) was obtained from metadata of acquired satellite images.

2.2.4.3 Scene

The DART scene is horizontally delimited by the landscape extension ($\Delta X, \Delta Y$) and vertically by the height of objects within the scenes and atmosphere layers (ΔZ). All simulated images were created using the same landscape extensions (20 x 30 m) relative to the plot extensions. In the simulated images of the *Eucalyptus grandis* stand, only the central subplot for each plot, with an area about 200 m², was analyzed to avoid border effects and to be precisely in the middle of the inventory plot. In order to analyze and compare the different

genotypes, one scene was simulated for each of the 16 different genotypes, 10 repetitions (blocks) and 4 plots for the *Eucalyptus grandis* stand at three different ages (4, 9 and 44 months).

Besides the size of the DART scenes and, since the objects in the scene are defined as voxels (tridimensional cells), the realism of simulations also depends on the spatial resolution of cells. In order to ensure the realism of the scene without increasing the computation time too much, small cubic voxel sizes of 0.25 x 0.25 x 0.25 cm were used.

2.2.4.4 Tree parameters

2.2.4.4.1 Trees dimensions

In order to reproduce the plantations based on precise information from forest field measurements, we opted to parameterize DART with exact positioning and dimensions of the simulated trees as input data. The positions of all the trees within each plot were generated based on the position of the trees visually extracted from a panchromatic WorldView-2 image in May, 2010 (0.5 m of spatial resolution). The exact tree dimensions necessary as input parameters in DART were described using interpolated values from the tree measurements calculated in the dates of forest inventories: height and diameter of the trunk below crown, trunk height within the crown, crown shape and geometric parameters related with crown shape. The composed ellipsoid was the crown type used to simulate the trees, which is a crown with two half ellipsoids (one for most of the crown and another for a possible small ellipsoid at the crown bottom).

2.2.4.4.2 Leaf Angle Distribution (LAD)

DART is able to use even types of predefined leaf angular distribution (LAD): planophile, erectophile, plagiophile, extremophile, uniform, ellipsoidal and elliptical. The ellipsoidal LAD, which uses a mean angle value as parameter input, was chosen because it simulates accurately *Eucalyptus* leaf angles distribution. The required parameter is the average leaf angles (ALA) and it was computed from the leaf angles measured *in situ* and interpolated for the specific dates. A different ALA was used for each crown section (top, middle and bottom) in the *E. grandis* stand and each treatment in the clonal test. A summary of the ALA used as input in DART for each date and treatment is shown in Table 3. We observe a large variability of LAD between clones, from values of ALA going from $\approx 27^\circ$ (planophile type) to $\approx 60^\circ$ (more erectophile type of angle distribution).

Table 3 - Average Leaf Angles (ALA) of the plots and treatments used as DART input per date of simulation

		ALA (°) ¹		
Stand / Treatment		May, 2010	Aug, 2010	July, 2013
<i>E. grandis</i>		24.61 (1.75)	32.25 (0.46)	40.17 (0.25)
Clonal test	1	37.95	37.95	39.57
	2	30.42	30.42	33.73
	3	25.54	25.54	27.06
	4	51.15	51.15	50.53
	5	50.49	50.49	49.56
	6	26.90	26.90	28.88
	7	44.00	44.00	44.92
	8	37.62	37.62	39.72
	9	51.17	51.17	50.66
	10	55.00	55.00	54.59
	11	43.36	43.36	43.08
	12	42.70	42.70	42.53
	12	41.94	41.94	42.34
	14	54.01	54.01	53.76
	15	27.26	27.26	30.28
	16	59.89	59.89	60.23

¹ Average of all crown levels and tree size (standard deviation) for *E. grandis* stand.

2.2.4.4.3 Leaf Area Index (LAI)

In the DART version, we used the leaf area index of the scene ($LAI_{scene} = LA_{specie} / \Delta X \cdot \Delta Y$, with $\Delta X = 20$ m and $\Delta Y = 30$ m) as an input parameter. The LAI can, however, be separated between the different species (defined in DART as each tree that has a specific LAI value) that constitute the scene. As we measured the leaf area of each tree in field (computed from allometric relationships— Section 2.3.2), each tree inside the plots was considered as a different species in DART. LAI values used as DART input are shown in Table 4.

Table 4 - Average Leaf Area Index (LAI) of the plots (*E. grandis* stand) and treatments (genotypes in the clonal test) used as DART input per date of simulation

		LAI (m ² /m ²)		
Stand / Treatment		May, 2010	Aug, 2010	July, 2013
<i>E. grandis</i>		0.93	1.48	3.63
Clonal test	1	0.63	0.91	4.57
	2	0.95	1.37	4.54
	3	0.65	0.94	4.91
	4	0.78	1.12	4.97
	5	0.58	0.83	4.93
	6	0.98	1.42	5.41
	7	0.82	1.18	4.37
	8	1.04	1.49	4.43
	9	0.79	1.13	4.88
	10	0.81	1.16	6.22
	11	0.96	1.38	6.07
	12	0.77	1.10	4.31
	12	0.83	1.19	5.46

2.2.4.4.4 Leaves, trunk and litter optical properties

The leaf, trunk and litter optical properties measured in the field (described in Section 2.2.2) were used as input optical properties of the simulated objects in DART. For leaves and litter optical properties, reflectance and transmittance for leaves and reflectance for litter were used field measurements carried out in October 2015. Trunk optical properties (reflectance) were based on field measurements in November 2010. Since we had several field measurements, we parameterized DART with optical properties respectively for each treatment and crown layer (lower, middle and upper levels) for leaves, each treatment for litter and one general trunk optical properties for all the eucalypt trees.

2.2.5 Atmospheric Correction

An atmosphere correction was necessary to simulate the bidirectional reflectance of images in top of atmosphere (TOA) using similar local atmosphere conditions that affect the real acquired satellite images. For that propose, we performed several simulations of atmosphere conditions to select the parameters that best described the real conditions. This procedure was done using the atmosphere module inside DART, which used pre-defined parameters of atmosphere databases (based on the Lowtran and Modtran models). The atmospheric parameters used in the simulation of the atmospheric radiation transfer were: aerosol (containing optical properties, vertical profile and Heyney Greenstein parameters), gas (containing optical properties, temperature profiles, O₃ and vertical profile of other gases and scale factors of vertical profile), band model correction (deltaTau1, deltaTAu2, Trans_UpDown), aerosol optical depth multiplicative factor (from 0.0 to 3.8) and water vapor content (from 0 to 3.8 cm). Since it was not possible to obtain measurements of all these atmospheric parameters at the satellite overpass time, we decided to calibrate these parameters through an inversion of the atmospheric module of DART based on the three acquired satellite images.

A simulated dataset of atmospheric effects was created by running the DART atmosphere module for many combinations of these parameters values and atmosphere options. These simulations were conducted for 21 bands (described in Section 2.3.4.1 above), in a homogeneous scene (1 x 1 m), with only ground reflectance varying from zero (total absorption) to one (total reflection). The outputs of the simulations were bidirectional reflectance at the bottom (BOA) and top of the atmosphere (TOA), totaling 8400 different simulations. For all these simulations, the sun and view zenithal and azimuthal angles corresponded to the angles of the real acquired satellite image (WorldView-2 images) in three

dates, which were adopted to compare the DART simulations. Twenty-one simulated bands were convolved to the multispectral broadbands of these satellite images.

After the creation of three datasets (one dataset for each date), linear regressions between the BOA and TOA reflectance were adjusted for each atmospheric condition and applied to the simulated BOA atmosphere in order to convert these simulated images from BOA to TOA. This procedure was much faster than directly simulating the *Eucalyptus* stand with atmosphere in the same DART simulation. These TOA images were compared with the real TOA from WorldView-2 satellite images. The best combination of parameters was selected according to the comparison that showed the smaller root mean square error (RMSE) for all bands.

After calibrations, the best set of atmospheric parameters were used in the atmosphere module of DART to simulate BOA and TOA images for each of the 21 bands and with virtual directions related with the geometry of acquisition of real satellite images.

2.2.6 WorldView-2 Satellite images

The satellite data used in this study to validate DART simulations were images obtained from the very high spatial resolution sensor WorldView-2. These images were obtained in May and August in 2010, and in July in 2013. The characteristics of satellite WorldView-2 are shown in Table 5 and the main acquisition parameters in Table 6.

Table 5 - Characteristics of WorldView-2 satellite

Launch	October, 2009	
Orbit	Sun synchronous	
	Altitude: 770 km	
	Period: 100 min	
Bands	Panchromatic: 450-800 nm	
	8 Multispectral:	
	Coastal: 400-450 nm	Red: 630-690 nm
	Blue: 450-510 nm	Red edge: 705-745 nm
	Green: 510-580 nm	Near infrared 1: 770-895 nm
	Yellow: 585-625 nm	Near infrared 2: 860-1040 nm
Spatial resolution	Panchromatic: 0.46 m nadir; 0.52 m off-nadir	
	Multispectral: 1.85 m nadir; 2.07 m off-nadir	
Swath Width	16.4 km nadir	

Adapted from: http://www.digitalglobe.com/sites/default/files/DG_WorldView2_DS_PROD.pdf.

Table 6 - Main acquisition parameters of Worlview-2 images

Date of acquisition	Acquisition time(GMT)	Sensor azimuth angle (°)	Sensor elevation angle (°)	Sun azimuth angle(°)	Sun elevation angle (°)
May, 2010	13:29	53.5	70.7	33.5	68.1
Aug, 2010	13:43	297.7	83.2	32.5	42.7
July, 2013	13:29	319.9	62.8	24.0	40.6

All the satellite images were orthorectified and projected on the Universal Transverse Mercator (UTM) Projected Coordinated System, Datum WGS-84 and Zone 22S. Polygons of each plot extension in the field were located in the images and stored in shapefiles. These shapefiles of rectangular plots were used as mask to extract the average radiance of plots from eight bands of each satellite images. Since we evaluated the reflectance of stands, the radiance values of the plots stored as Digital Numbers were converted to TOA reflectance values using the parameters and equations defined in the metadata files of images and procedure described in DIGITALGLOBE (2010). The mean TOA reflectance of each plot/genotype, block and date of the three WorldView-2 images were computed to be further compared with the simulated DART TOA reflectance images.

2.2.7 Realism of simulated scenes in DART

To verify the realism of DART simulations, we visually checked if the DART tridimensional views were adequately represented due to the input of datasets. In these analyses, we verified if the shape, size and positions of the trees inside the scenes for each date in the tridimensional views were visually compatible with information of field measurement and input data, such as height, type and dimensions of crowns and distribution inside the plots. Leaf area index (LAI) used in DART- from input LAI values - to perform the modeling of each plot was compared to the entire-plot LAI measured in the field.

2.2.8 Comparison between simulated and satellite images

The accuracy of the simulated reflectance images at the top of atmosphere (TOA) from DART was checked against the TOA reflectance obtained from real acquired WorldView-2 images, for all 8 bands (coastal, blue, green, yellow, red, red edge, NIR1 and NIR2), three ages (6, 9 and 44 months) and all 16 clones (average of the 10 blocks). This comparison was performed using the mean reflectance of DART images that were convolved to Worldview-2 8 bands according to their sensor spectral response, and the mean reflectance of Worldview-2 images at the TOA level. The accuracy level was expressed by the mean absolute error

(MAE) (Equation 3) as suggested by Willmott and Matsuura (2005) to assess the average model performance and identify the best and worst simulated band:

$$MAE_{\lambda} = \frac{1}{n} \sum_1^n |R_{WV2(\lambda)} - R_{DART(\lambda)}| \quad (3)$$

Where: $R_{WV2(\lambda)}$ is the measured reflectance by Worldview-2 satellite at wavelength λ , $R_{DART(\lambda)}$ is the reflectance simulated by DART in the same wavelength and n is the number of samples ($n=480$, being 3 dates, 10 blocks and 16 clones).

Additionally, a comparison between all clones reflectance from DART simulations and Worldview-2 bidirectional reflectance at BOA images was performed to analyze the differences of clones related to their reflectance behavior on remote sensing images.

3 Results and Discussion

3.2.1 Optical properties and chlorophyll content

Trunk optical properties (reflectance) measured in 2010 and litter optical properties (reflectance) measured 2015, which were used as input for all DART simulations, are shown in Figure 4. The *Eucalyptus* trunk reflectance showed lower reflectance in the red region of the spectrum, suggesting the presence of absorption by chlorophyll pigments. Then, it had higher reflectance values in the near infrared region and, afterward, it showed some absorption in higher wavelength region characterized by wood elements properties and water content. Some noise at the beginning of the visible region was attributed to the procedure for *in situ* data collection. Litter reflectance for each clone (Figure 4b) showed similar pattern for all clones characterized by low reflectance in the visible region and increasing curve along the spectrum, with a mild absorption peak in the water absorption band (1400 nm) (JENSEN, 2005). The abrupt shift of reflectance in the near infrared region for some clones (e.g. genotypes 3 and 4) was attributed to the sensibility of the Contact Probe to collect the samples during *in situ* measurements. Reflectance intensity varied between genotypes, mainly in the near infrared region, where genotype 2 presented the highest reflectance and genotype 11 had the lowest reflectance in this region. These differences in litter reflectance are related to the different composition of litter materials (e.g. green and dead leaves, bark and branches) and their specific spectral properties in each genotype and reinforce the potential to use specific data for each genotype to better describe the reality of the stand.

Leaf optical properties (reflectance) for each clone are shown in Figures 5, 6 and 7, respectively, for bottom, middle and top of the crown layer. We presented only the results of field collection in 2015. Figures 5a, 6a and 7a show the whole spectrum of visible and near

infrared region. Figures 5b, 6b and 7b show the reflectance around visible region (mainly blue and red) and Figures 5c, 6c and 7c show the reflectance around near infrared region. The curve shapes for all crown layers were very similar and with general characteristics of green leaves spectral reflectance, with absorption peaks in the blue and red regions in the visible domain due to leaf pigments such as chlorophylls, carotene and xanthophylls (PONZONI; SHIMABUKURO, 2007), higher and relatively constant reflectance in the near infrared region with smooth absorption around 980 and 1200 nm caused by water vapor absorption (SIMS; GAMON, 2003; TUCKER, 1978), and an absorption peak in the water absorption band (1400 nm) in the mid infrared (MID) region.

Despite some variations, leaves in the crown layers showed a very similar reflectance pattern. Genotypes 3 and 5 had the highest absorption in the blue and red regions (Figures 5b, 6b and 7b), which is the region related with leaf pigments. Comparing this behavior of reflectance in the visible region with chlorophyll content measured with SPAD (Figure 8), it was not possible to confirm that the higher absorption was caused by chlorophyll amount (TAGEEVA et al., 1960; THENKABAIL et al., 2000) since genotypes 3 and 5 did not show higher values of SPAD measurements, with some exceptions for genotype 3 that showed a relative high chlorophyll amount. Some studies also found results showing that the reflectance of evergreen Eucalyptus leaves in the green, blue and red regions was not sensitive to variation in chlorophyll content as observed in the red edge region (DATT, 1998; 1999). Since SPAD showed only relative chlorophyll content, other leaf pigments could explain its absorption differences (USTIN et al., 2009). Moreover, this comparison is also difficult to establish, since SPAD measurements were not made in the same leaves where optical properties were collected. The different absorption between clones in the visible region could also be explained by differences in the leaf moisture amount (DATT, 1999) and thickness, even because genotypes 3 and 5 showed a relative higher absorption throughout almost all analyzed spectrum.

It was not possible to clearly define a reflectance pattern between clones in the near infrared region, because it changed between layers. The top crown layer showed the highest variability between and within clones (Figure 7), probably because of the predominance of young leaves. These differences of optical properties can be related with internal differences in mesophyll structures between clones and, within each clone, differences between leaf positions in the crown layers (ASHTON et al., 1998; CLARK et al., 2005; PANDITHARATHNA et al., 2008). We compared our results with the findings of Nogueira (2014), who did the leaf anatomical characterization (in the central part of the leaves) of

these 16 genotypes in the same clonal test between 2012 and 2013; however, it was not possible to conclude the type of relationship between leaf optical properties and anatomical leaf characteristics. Detailed work should be performed using the same samples to have a better conclusion about this relationship.

Considering the chlorophyll content in leaves measured with the SPAD device in 2010 (Figure 8, filled circles) and in 2014 (asterisks), higher inter-clonal differences in their values were found for the top crown layer (Figures 8e and f). Again, because of the predominance of young leaves at different dynamics of development stages that could affect leaf anatomy and physiology (ENGLAND; ATTIWILL, 2011). No differences in the SPAD values were found between internal and external leaves for both dates (2010 and 2014, respectively, asterisk and filled circle) and crown layers (Figures 8a, c and e at the external crown area and Figures 8b, d and f near the trunk). Comparing SPAD values between crown layers, we can see that the chlorophyll content (per unit surface of leaves) was decreasing from bottom to top layer, also due to the anatomical and physiological differences between mature leaves, predominant at the bottom, and young leaves, predominant at the top. Lastly, in terms of the chlorophyll content differences between genotypes, genotypes 1, 2 and 14 showed, in general, the highest SPAD values. Genotypes 1 and 2 are the treatments with seminal origin, which may introduce the hypothesis that clonal genotypes - normally introduced to obtain yield increase - would have to come from improved photosynthetic efficiency through a reduction in leaf chlorophyll per unit area (ZHU et al., 2010; HAMBLIN et al., 2014). According to Zhu et al. (2014), the reasons to explain why reduced chlorophyll levels might benefit plants are less chlorophyll per unit leaf area that would improve light transmission through the canopy, potentially increasing photosynthesis of lower leaves and, when exposed to excess light, more transparent leaves that would reduce the level of photochemical damage to chloroplasts and less energy that would be required for their repair.

Figure 4 - Trunk optical properties (reflectance) of the study area collected on 2010 (a) and litter optical properties (reflectance) (b) for each clone collect on 2015

Figure 5 - Leaf optical properties (reflectance) at bottom crown layer for 16 clones within the spectrum range between 350 and 1500 nm (a), zoom in the visible region (b) and zoom in the near infrared (c)

Figure 6 - Leaf optical properties (reflectance) at middle crown layer for 16 clones in the spectrum range between 350 and 1500 nm (a), zoom in the visible region (b) and zoom in the near infrared (c)

Figure 7 - Leaf optical properties (reflectance) at top crown layer for 16 clones in the spectrum range between 350 and 1500 nm (a), zoom in the visible region (b) and zoom in the near infrared (c)

Figure 8 - SPAD values of chlorophyll amount collected in 2010 (asterisk) and 2014 (filled circle) for leaves in the external crown area (left) and near the trunk (right) at the bottom (a and b), middle (c and d) and top (e and f) crown layer

3.2.2 Atmospheric correction

An example of the simulated TOA reflectance in the 7200 different atmospheric conditions used to calibrate the atmospheric parameters and the Worldview-2 TOA reflectance on the *E. grandis* plots in all 9 bands (8 multispectral + 1 panchromatic bands) at 6 months of age (May, 2010) are shown in Figure 9. The simulated TOA reflectance reached all the Worldview-2 TOA reflectance values with a wide range of possible values. It means that DART atmospheric simulations can greatly change the BOA reflectance through the atmosphere layer. Also, the range of the tested atmospheric conditions included well the

Worldview-2 TOA reflectance (RMSE=0.42), including in the coastal and blue bands, which are rather sensitive to atmospheric conditions (respectively, bands 1 and 2) (TARANTINO et al., 2012).

The combinations of parameters that better described the atmospheric conditions were chosen by group with RMSE equal to 0.042 (smallest value), comprising the TROPICAL model for gases, RURAL23 Km model for aerosols and Trans_UpDown for band model correction. The aerosol optical depth multiplicative factor and the precipitable water amount vary according to the date. These combinations of atmospheric parameters were used to compute the TOA images in DART.

Figure 9 - Reflectance of the TOA images simulated in DART using all the combination of atmospheric parameters (blues asterisks) and reflectance of TOA images of Worldview-2 (black asterisks) for each band (multispectral - 1 to 8, panchromatic - 9) in May, 2010. This figure represents an example of the behavior of the TOA images varying according to atmospheric conditions

3.2.3 Structural analysis of simulated trees

To visually verify the positions, shapes and sizes of the trees in DART simulations, the DART 3D view tool was used for one plot of *E. grandis* stand and one block in the clonal test for all dates (Figures 10 and 11, respectively). These images allowed to check and to analyze how the simulated trees were represented in the model. The shape, size and position of the trees were realistic with the trees in the field, showing that the input parameters and their translation in the DART to build the scenes were coherent.

The LAI values used in DART scene were similar to the *in situ* measured LAI for the *E. grandis* stand (Figure 12a, $R=0.994$) and clonal test (Figure 12b, $R=0.996$), with RMSE equal to 0.1682, 0.2650 and 0.1438, respectively, at 6, 9 and 44 months of age for *E. grandis* stand and 0.042, 0.0562 and 0.4693 for the clonal test. The LAI computed in the DART from the LAI used as input did not correspond exactly to the LAI extracted from the *in situ* measurements, mainly because DART considers the LAI of each tree distributed of each voxel of this respective tree and according to the DART scene dimension. The lower value of LAI within the DART scene compared to the *in situ* measurements could be explained by the DART procedure to build the scenes, which respects the scene dimensions and cuts the crown area of the trees in the extreme position of the plot that leaves the scene area and, therefore, generates lower values in the scene than the input of LAI values (since the crown area of the trees in the border is cut). It did not occur in the first two dates because the crown area of the trees in the extreme positions did not leave the scene dimensions. Besides these small discrepancies, LAI results corroborate DART suitability to translate input parameters to build realistic vegetation objects in a scene as well as the appropriate use and adaptation of field measurements to parameterize the model.

Figure 10 - Aerial (left) and perspective view (right) of DART simulated scene of plot 1 in the *E. grandis* stand at 6 (a and b), 9 (c and d) and 44 (e and f) months of age

Figure 11 - Aerial (left) and perspective view (right) of DART simulated scene of treatment 1, clone 1 in the clonal test at 6 (a and b), 9 (c and d) and 44 (e and f) months of age

Figure 12 - Measured and computed leaf area index (LAI) by DART of *E. grandis* stand (a) and clonal test (b) at 6 (May, 2010), 9 (August, 2010) and 44 (July, 2013) months of age

3.2.4 Analysis of DART simulated images

The mean reflectance simulated by DART and acquired by the Worldview-2 images at the eight multispectral bands (Table 5) are shown in Figures 13, 14 and 15, respectively, for the plots in the *E. grandis* stand, genotypes 1 to 8 and genotypes 9 to 16 for the clonal test (average for all blocks) at six (May 2010, dotted line), nine (August 2010, dashed line) and 44 (July 2013, line) months of age. In general, the mean TOA reflectance from DART simulations showed a good agreement with the mean TOA reflectance of the images from Worldview-2 satellite for the bands in the visible region in all dates and all plots and genotypes. More pronounced discrepancies were found in the comparison of bands in the near infrared region (bands NIR1 and NIR2 in Figures 13, 14 and 15). The plots in the *E. grandis* stand (Figure 13) showed greater differences in the NIR1 band than the clonal test did, mainly, for plot 1 and when the trees were at 44 months of age (July, 2013). The clonal test (Figures 14 and 15) also presented greater differences in the near infrared in July, 2013.

In terms of bi-direction reflectance, in this study, the comparison between simulated and real satellite images from forest stands is still a difficult task, since the average signal of the image is dominated by the macroscopic properties of the illuminated and shadowed crowns as well as ground surface (COUTURIER et al., 2008). Considering this aspect, the pixel size and model capacity to assess the elements of forest heterogeneity of the crown and the understory spectral signature are important factors. In this study, the pixel size 0.25 m and the massive input information of trees, such as location, crown size and parameters from

different layers and optical properties of leaves, trunk and background surface (litter) were very representative of the reality of stands, which was shown in the reflectance values compared with the real reflectance from Worldview-2 images. The potential of the DART model to simulate the reflectance of heterogeneous natural landscapes has been successfully tested comparatively with other radiative transfer models for over 15 years throughout the Radiative Transfer Model Intercomparison exercise (RAMI) (WIDLÓWSKI et al., 2015). However, the simplifying assumption of the crowns composed of ellipsoids used here as DART input could limit the resemblance of simulated images with the reality of the canopy structure and, consequently, with images from very high resolution satellite images, as Worldview-2. Although, the level of complexity required for a more exact description of canopy must be contrasted with the need for detailed input parameters, nevertheless, it is a very difficult task to perform in the reality of forest studies. We used a massive database with parameters as DART input collected from several field campaigns. In the same study site, new measurements comprised terrestrial laser scanning for building mockup objects representative of the trees to be used in the DART model and new comparison between these two approaches should be performed in the future.

A numerical comparison between the mean reflectance simulated from DART and from Worldview-2 images was performed using the Mean Absolute error (MAE) together for all blocks and genotypes of the clonal test. The MAE value for all bands and dates is shown in Figure 16. Generally, MAE values were low for all bands. The lowest values were found for the bands in the visible region (< 0.016) and NIR2 band (0.006) and higher for the NIR1 band (0.045). These results reinforced the good agreement of DART to model the reflectance of *Eucalyptus* forest stands at different ages and genotypes. Despite the continuous comparison of DART performance over the years in the RAMI exercise (PINTY et al, 2004; WIDLÓWSKI et al., 2015), the comparison of our results with other studies is limited due to different approaches performed under several forest types and local conditions.

Figure 13 - DART (black circles) and WorldView-2 (hollow circles) reflectance of eight bands (1=coastal, 2=blue, 3=green, 4= yellow, 5= red, 6=red edge, 7=NIR1 and 8=NIR2) for the *E. grandis* plots (1 to 4) at 6 (dotted line), 9 (dashed line) and 44 (line) months of age

Figure 14 - DART (black circles) and WorldView-2 (hollow circles) reflectance of eight bands (1=coastal, 2=blue, 3=green, 4= yellow, 5= red, 6=red edge, 7=NIR1 and 8=NIR2) for the genotypes 1 to 8 at 6 (dotted line), 9 (dashed line) and 44 (line) months of age

Figure 15 - DART (black circles) and WorldView-2 (hollow circles) reflectance of eight bands (1=coastal, 2=blue, 3=green, 4= yellow, 5= red, 6=red edge, 7=NIR1 and 8=NIR2) for the genotypes 9 to 16 at 6 (dotted line), 9 (dashed line) and 44 (line) months of age

Figure 16 - Absolute Mean Average Error between DART and Worldview-2 reflectance for the eight bands (bands 1=coastal, 2=blue, 3=green, 4= yellow, 5= red, 6=red edge, 7=NIR1 and 8=NIR2) for all dates

Regarding higher discrepancies between DART and Worldview-2 mean reflectance of the NIR1 band, more detailed analysis of this relationship of the clonal test in all dates are shown in Figure 17. DART underestimated the mean reflectance for all dates in the NIR1 band (770-785 nm, Figure 17), more pronounced at 44 months of age (July 2013). No trends were found for each genotype or block specifically (results not shown here). The not-well simulation of the intra-crown and ground projecting shadow effect on simulated images could be one explanation for this underestimation. This limitation to simulate the dark side of the scene may have happened both because a DART limitation and/or problems to translate vertical and horizontal leaf distribution inside the crown as input parameters and/or the canopy porosity that was not adequately assessed by the turbid representation of the canopy. In May and August 2010, there was an image of the majority of soils in regions in the scenes, since the trees were small (respectively, 6 and 9 months of age) without overlapping between crowns both intra- and inter-rows of the stands. However, in July 2013, more complex tree structures with higher tree height and canopy dimensions led to a higher shadow effect on neighboring trees and self-shadowing, which contributed to decreasing the mean reflectance of the scene. A detailed analysis was carried out in this topic to precisely address the NIR1 band greater discrepancy. Despite unsatisfactory results in the NIR1 band, since the results

were systematic underestimated for all simulations without specific tendency for the genotypes and blocks, a post-processing could be applied to simulated images to correct these reflectance values.

Figure 17 - DART and Worldview-2 reflectance in the near infrared bands simulated and acquired in May 2010 (asterisk), August 2010 (cross) and July 2013 (point) between 770-785 nm (NIR1)

Additionally, the reflectance analysis between genotypes in all dates for visible and near infrared regions were performed and presented in Figure 20, where the DART (top, Figures 18a,b and c) and Worldview-2 (bottom, Figures 18d, e and f) multispectral BOA reflectance for all genotypes at six (Figures 18a and d), nine (Figures 18b and e) and 44 (Figures 18c and f) months of age in the clonal test are presented. The effect of different genotypes was pronounced mainly on the NIR bands for both DART and Worldview-2 images and even more when the trees were at 44 months of age (July 2013), suggesting that the structural variability of the stand was the main factor to address these differences and, not necessarily, the chlorophyll content (Figure 8). Both simulated and acquired images showed almost the same reflectance hierarchy between genotypes in all dates. At six (Figures 18a and d) and nine (Figures 18b and e) months of age, genotype 8 showed the highest reflectance in the near infrared region. This genotype was the treatment with greater leaf area and crown diameter values in these same dates (Figure 3), suggesting the impact of these parameters to address canopy reflectance behavior in satellite images. Genotype 8 also presented a high

average DBH and tree height values in these ages, which showed fast growth potential of this genotype at the beginning of stand establishment also translated by the BOA reflectance - with lower reflectance in the visible region and higher, in the near infrared region. It reinforces DART suitability to describe the radiative transfer in forest landscapes at different ages. At 44 months of age (Figures 18c and f), it was not possible to establish a clear relationship between DART and Wordview-2 reflectance of the clones in the near infrared bands, possibly due to the already mentioned issues concerning limitations of simulations in the NIR1 band. However, genotypes 10 and 11 that showed the highest reflectance in the near infrared region at 44 months of age (Figures 18c and f), respectively, for DART simulations and Wordview-2 images also presented the highest leaf area values at this age, corroborating the effects of this parameter on reflectance.

Since DART simulations were well-performed compared with real acquired satellite images, the whole and detailed simulated database and new other simulations in different conditions of the structural characteristics of eucalyptus stands and satellite acquisition conditions could be performed to explore several approaches of these genotypes related with their biophysical parameters (e.g. estimate LAI, evaluate leaf angle effect, estimate fAPAR, among others) and satellite conditions (e.g. effect of view direction and sun geometry). The evaluation of DART simulations carried out in this study by comparing with real satellite images represented a first step to intensify more studies to better address the relationship between canopy reflectance and biophysical parameters using radiative transfer models, such as the DART.

Figure 18 - Multispectral reflectance simulated from DART (a, b and c) and acquired from Worldview-2 satellite (d, e and f) for all genotypes at 6 (a and d), 9 (b and e) and 44 (c and f) months of age. First graphic shows an example of the multispectral band names and locations to build the lines

4 Conclusions

This study proposed to analyze the accuracy of DART simulations in terms of biological realism and canopy reflectance of eucalyptus plantations over specific ages compared with very high-resolution satellite images obtained from the Worldview-2 sensor.

Optical properties and structural variables of the trees used as input in the DART model showed a great difference between 16 clones described in this study and reinforces the potential to study the effect of these characteristics on reflectance simulation.

DART allowed to proceed to a robust and accurate atmosphere correction of images (RMSE = 0.042).

DART was accurate to simulate the reflectance of bands in the visible region of the analyzed spectrum (MAE<0.016). However, some limitations were found in the simulations of bands in the near infrared band (NIR1 band - 770-785 nm), mainly at 44 months of age (MAE=0.045).

It was not possible to conclude the causes for NIR1 underestimation, but it could be associated with errors in shadow modelling. Despite these limitations, the systematic errors in the near infrared bands did not make DART usage impossible, since post-processing techniques could be implemented.

Similar reflectance hierarchy between genotypes for DART and Worldview-2 multispectral bottom of atmosphere (BOA) level reinforces the DART suitability to describe the radiative transfer to forest landscapes at different ages. The more pronounced effect of the genotypes on the NIR bands suggests that the structural variability of the stand was the main factor to address these differences and, not necessarily, the chlorophyll content.

Higher reflectance in the near infrared region at BOA level for genotypes with greater leaf areas at the specific date reinforces the effect of this parameter on canopy reflectance of eucalyptus stands.

DART simulations were well performed compared with real acquired satellite images and, consequently, simulated database could be performed to explore several approaches of these genotypes related with their biophysical parameters and satellite conditions.

References

- ASHTON, P.M.S.; OLANDER, L.P.; BERLYN, G.P.; THADANI, R.; CAMERON, I.R. Changes in leaf structure in relation to crown position and tree size of *Betula papyrifera* within fire-origin stands of interior cedar-hemlock. **Canadian Journal of Botany**, Ottawa v. 76, n. 7, p. 1180–1187, 1998.
- BANSKOTA, A.; SERBIN, S.P.; WYNNE, R.H.; THOMAS, V.A.; FALKOWSKI, M. J.; KAYASTHA, N.; GASTELLU-ETCHEGORRY, J-P.; TOWNSEND, P.A. An LUT-Based Inversion of DART Model to Estimate Forest LAI from Hyperspectral Data. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, New York, Lop. 1–14, 2015.
- CAMPOE, O.C.; STAPE, J.L.; LACLAU, J.P.; MARSDEN, C.; NOUVELLON, Y. Stand-level patterns of carbon fluxes and partitioning in a *Eucalyptus grandis* plantation across a gradient of productivity, in Sao Paulo State, Brazil. **Tree physiology**, Oxford, v. 32, n. 6, p. 696–706, June 2012.
- CAMPOE, O.C.; STAPE, J.L.; NOUVELLON, Y.; LACLAU, J-P.; BAUERLE, W.L.; BINKLEY, D.; LE MAIRE, G. Stem production, light absorption and light use efficiency between dominant and non-dominant trees of *e.grandis* across a productivity gradient in Brazil. **Forest Ecology and Management**, Amsterdam, v. 288, p. 14–20, 2013.
- CARRER, D.; ROUJEAN, J.L.; LAFONT, S.; CLAVET, J.C.; BOONE, A.; DECHARME, B.; DELIRE, C.; GASTELLU-ETCHEGORRY, J.P. A canopy radiative transfer scheme with explicit FAPAR for the interactive vegetation model ISBA-A-gs: impact on carbon fluxes. **Journal of Geophysical Research: Biogeosciences**, Hoboken, v. 118, n. 2, p. 888–903, June 2013.
- CENTRE D'ETUDES SPATIALES DE LA BIOSPÈRE. **DART handbook**. Toulouse, 2013a. 97 p.
- _____. **DART modules user manual**. Toulouse, 2013b. 54p.
- _____. **DART user manual**. Toulouse, 2014. 142 p.
- CHOPPING, M.; MOISEN, G.G.; SU, L.; LALIBERTE, A.; RANGO, A.; MARTONCHIK, J.V.; PETERS, D.P.C. Large area mapping of southwestern forest crown cover, canopy height, and biomass using the NASA Multiangle Imaging Spectro-Radiometer. **Remote Sensing of Environment**, New York, v. 112, n. 5, p. 2051–2063, 2008.
- CLARK, M.; ROBERTS, D.; CLARK, D. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. **Remote Sensing of Environment**, New York, v. 96, n. 3/4, p. 375–398, June 2005.
- COUTURIER, S.; GASTELLU-ETCHEGORRY, J-P; PATIÑO, P.; MARTIN, E. A model-based performance test for forest classifiers on remote-sensing imagery. **Forest Ecology and Management**, Amsterdam, v. 257, p. 23–37, 2009.

DA SILVA, E. V.; BOUILLET, J-P.; GONÇALVES, J. L. M.; ABREU JUNIOR, C. H.; TRIVELIN, P. OCHEUZE, C.; HINSINGER, P.; JOURDAN, C.; NOUVELLON, Y.; STAPE, J. L.; LACLAU, J-P. Functional specialization of Eucalyptus fine roots: contrasting potential uptake rates for nitrogen, potassium and calcium tracers at varying soil depths. **Functional Ecology**, Oxford, v. 25, n. 5, p. 996–1006, Oct. 2011.

DARVISHZADEH, R.; SKIDMORE, A.; SCHLERF, M.; ATZBERGER, C. Inversion of a radiative transfer model for estimating vegetation LAI and chlorophyll in a heterogeneous grassland. **Remote Sensing of Environment**, New York, v. 112, n. 5, p. 2592–2604, May 2008.

DATT, B. Remote sensing of chlorophylla, chlorophyllb, chlorophyll a+b, and total carotenoid content in *Eucalyptus* leaves. **Remote Sensing of Environment**, New York, v.66, p. 111-121, 1998.

_____. Remote sensing of water content in *Eucalyptus* leaves. **Australian Journal of Botany**, Melbourne, v. 47, n. 6, p. 909–923, 1999.

DIGITALGLOBE. **The benefits of the eight spectral bands of worldview-2**. 2010. 12 p.

ENGLAND, J.R.; ATTIWILL, P.M. Changes in stomatal frequency, stomatal conductance and cuticle thickness during leaf expansion in the broad-leaved evergreen species, *Eucalyptus regnans*. **Trees**, Berlin, v. 25, n. 6, p. 987–996, 2011.

GASTELLU-ETCHEGORRY, J-P. 3D modeling of satellite spectral images, radiation budget and energy budget of urban landscapes. **Meteorology and Atmospheric Physics**, Wien, v. 102, n. 3/4, p. 187–207, Dec. 2008.

GASTELLU-ETCHEGORRY, J-P.; BRUNIQUET-PINEL, V. A modeling approach to assess the robustness of spectrometric predictive equations for canopy chemistry. **Remote Sensing of Environment**, New York, v. 76, n. 1, p. 1–15, Apr. 2001.

GASTELLU-ETCHEGORRY, J-P.; TRICHON, V. A modeling approach of PAR environment in a tropical rain forest in Sumatra: application to remote sensing. **Ecological Modelling**, Amsterdam, v. 108, n. 1/3, p. 237–264, May 1998.

GASTELLU-ETCHEGORRY, J-P.; MARTIN, E.; GASCON, F. DART: a 3D model for simulating satellite images and studying surface radiation budget. **International Journal of Remote Sensing**, Basingstoke, v. 25, n. 1, p. 73–96, Jan. 2004.

GASTELLU-ETCHEGORRY, J-P.; ZAGOLSKI, F.; ROMIER, J. A simple anisotropic reflectance model for homogeneous multilayer canopies. **Remote Sensing of Environment**, New York, v. 57, p. 22–38, 1996.

GOBRON, N.; PINTY, B.; VERSTRAETE, M.M. Theoretical limits to the estimation of the leaf area index on the basis of visible and near-infrared remote sensing data. **IEEE Transactions on Geoscience and Remote Sensing**, New York, v. 35, n. 6, p. 1438–1445, 1997.

GUILLEVIC, P. Modeling BRF and radiation regime of boreal and tropical forest : II . PAR Regime. **Remote Sensing of Environment**, New York, v. 340, p. 317–340, 1999, July 1998.

HAMBLIN, J.; STEFANOVA, K.; ANGESSA, T.T. Variation in chlorophyll content per unit leaf area inspring wheat and implications for selection insegregating material. **PLoS ONE**, San Francisco, v. 9, n. 3, p. 1-9, March, 2014.

INDÚSTRIA BRASILEIRA DE ÁRVORES. **Relatório IBÁ**.Brasília, 2015.

INSTITUTO DE PESQUISAS E ESTUDOS FLORESTAIS. **Relatório anual IPEF 2012**.Piracicaba, 2012.

JENSEN, J.R. **Introductory digital image processing: a remote sensing perspective**. Prentice Hall, 2005.

LACLAU, J.P.; BOUILLET, J.P.; GONÇALVES, J.L.M; SILVA, E.V.; JOURDAN, C.; CUNHA, M.C.; SMOREIRA, M.R.; SAINT-ANDRÉ, L.; MAQUÈRE, V.;NOUVELLON, Y.;RANGER, J. Mixed-species plantations of *Acacia mangium* and *Eucalyptus grandis* in Brazil. **Forest Ecology and Management**, Amsterdam, v. 255, n. 12, p. 3905–3917, June. 2008.

NOGUEIRA, R.I. **Caracterização anatômica foliar de 16 genótipos de *Eucalyptus* de alta produtividade do Brasil**. 2014. 114 p. Dissertação (Mestrado em Engenharia Florestal) - Faculdade de Ciências Agrônômicas, Universidade Estadual Paulista “Júlio de Mesquita Filho”, Botucatu, 2014.

PANDITHARATHNA, P.A.K.A.K.;SINGHAKUMARA, B.M.P.;GRISCOM, H.P.; ASHTON, M.S. Change in leaf structure in relation to crown position and size class for tree species within a Sri Lankan tropical rain forest. **Botany**, Oxord, v. 86, n. 6, p. 633–640, 2008.

PINTY, B., WIDLowski, J-L.; TABERNER, M.; GOBRON, N.; VERSTRAETE, M.M.; DISNEY, M.; GASCON, F.; GASTELLU-ETCHEGORRY, J-P.; JIANG, L.; KUUSK, A.; LEWIS, P.; LI, X.; NI-MEISTER, W.; NILSON, T.; NORTH, P.; QIN, W.; SU, L.; TANG, S.; THOMPSON, R.; VERHOEF, W.; WANG, H.; WANG, J.; YAN, G.; ZANG H. RAdition transfer Model Intercomparison (RAMI) exercise: results from the second phase. **Journal of Geophysical Research**, Washington, v. 109, p. 1-19, 2004.

PONZONI, F.J.; SHIMABUKURO, Y.E. **Sensoriamento remoto no estudo da vegetação**.São José dos Campos: INPE, 2007.

SIMS, D.A.; GAMON, J.A. Estimation of vegetation water content and photosynthetic tissue area from spectral reflectance: a comparison of indices based on liquid water and chlorophyll absorption features. **Remote Sensing of Environment**, New York, v. 84, n. 4, p. 526–537, 2003.

STAPE, J.L.; BINKLEY, D.; GRATTAPAGLIA, D.; CAMPOE, O.; ALVARES, C; GOMES, F.; MATTOS, E.; OTTO, M.; HAKAMADA, R.; MORAES, M.T. Fatores hídricos e as decisões de silvicultura, de melhoramento e de proteção na eucaliptocultura. In:ENCONTRO BRASILEIRO DE SILVICULTURA, 2014.**Proceedings...**, p. 81–98.

TAGEEVA, S.V; BRANDT, A.B.; DEREVJANKO, V.G. Changes in the optical properties of leaves during the growing season. **Doklady Akademii nauk SSSR**, Leningrad, v. 135, n. 5, p. 1270–1273, 1960.

TARANTINO, C.; ADAMO, M.; PASQUARIELLO, G.; LOVERGINE, F.; BLONDA, P.; TOMASELLI, V. 8-band image data processing of the Worldview-2 satellite in a wide area of applications. **Earth Observation**, Luxembourg, p. 137–152, 2012.

THENKABAIL, P.S.; SMITH, R.B.; DE PAUW, E. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. **Remote sensing of Environment**, New York, v. 71, n. 2, p. 158–182, 2000.

TUCKER, C.J. A comparison of satellite sensor bands for vegetation monitoring. **Photogrammetric Engineering and Remote Sensing**, Maryland, v. 44, n. 11, 9. 1369-1380, 1978.

USTIN, S.L.; GITELSON, A.A.; JACQUEMOUD, S.; SCHAEPMAN, M.; ASNER, G.P., GAMON, J.A.; ZARCO-TEJADA, P. Retrieval of foliar information about plant pigment systems from high resolution spectroscopy. **Remote Sensing of Environment**, New York, v. 113, p. S67–S77, 2009.

VERSTRAETE, M.M.; GOBRON, N.; AUSSDAT, O.; ROBUSTELLI, M.; PINTY, B.; WIDLOWSKI, J-L.; TABERNER, M. An automatic procedure to identify key vegetation phenology events using the JRC-FAPAR products. **Advances in Space Research**, Oxford, v. 41, n. 11, p. 1773–1783, Jan. 2008.

WIDLOWSKI, J-L.; MIO, C.; DISNEY, M.; ADAMS, J.; ANDREDAKIS, I.; ATZBERGER, C.; BRENNAN, J.; BUSETTO, L.; CHELLE, M.; CECCHERINI, G.; COLOMBO, R.; CÔTÉ, J-F.; EENMÄE, A.; ESSERY, R.; GASTELLU-ETCHEGORRY, J-P.; GOBRON, N.; GRAU, E.; HAVERD, V.; HOMOLOVÁ, L.; HUANG, H.; HUNT, L.; KOBAYASHI, H.; KOETZ, B.; KUUSK, A.; KUUSK J.; LANG, M.; LEWIS, P.E.; LOVELL, J.L.; MALENOVSKÝ, Z.; MERONI, M.; MORSDORF, F.; MÖTTUS, M.; NI-MEISTERZ, W.; PINTY, B.; RAUTIAINEN, M.; SCHLERF, M.; SOMERS, B.; STUCKENS, J.; VERSTRAETEAE, M.M.; YANG, W.; ZHAO, F.; ZENONE, T. The fourth phase of the radiative transfer model intercomparison (RAMI) exercise: actual canopy scenarios and conformity testing. **Remote Sensing of Environment**, New York, v. 169, p. 418-437, 2015.

WILLMOTT, C.J.; MATSUURA, K. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. **Climate Research**, Oldendorf, v. 30, n. 1, p. 79–82, 2005.

ZHANG, Q.; MIDDLETON, E.M.; MARGOLIS, H.; DROLET, G.G.; BARR, A.; BLACK, T.A. Can a satellite-derived estimate of the fraction of PAR absorbed by chlorophyll (FAPARchl) improve predictions of light-use efficiency and ecosystem photosynthesis for a boreal aspen forest? **Remote Sensing of Environment**, New York, v. 113, n. 4, p. 880–888, 2009.

ZHU, X-G.; LONG, S.P.; ORT, D.R. Improving photosynthetic efficiency for greater yield. **Annual Review of Plant Biology**, Palo Alto, v. 61, 2010.

3 RELATIONSHIP BETWEEN LEAF AREA INDEX AND SPECTRAL VEGETATION INDICES IN EUCALYPTUS STANDS USING VERY HIGH SPATIAL RESOLUTION SIMULATED IMAGES FROM THE DART MODEL

Abstract

The leaf area index (LAI) of forest plantations is a key biophysical parameter implied in different carbon and water cycle processes of forest ecosystems, including biomass production. There are many methods to retrieve LAI from remote sensing images, divided into empirical methods (e.g. using spectral vegetation indices – SVI's calibrated by *in situ* measurements) and the method that uses radiative transfer model (RTM). Each method has its own advantages and limitations that depend mainly on the type of ecosystem under study, available *in situ* data, etc., and on the reach to different precision levels to estimate LAI. Some limitations can be overcome using a combination of these two methods, also called the hybrid method. This study used a hybrid method to investigate the possibility to estimate a relationship between spectral vegetation indices and LAI on a variety of genotypes and ages of eucalyptus forest plantations from RTM simulations. The DART model was calibrated with extensive field measurements and was used to simulate spectral reflectance of the canopy for different view configurations, sun angles, and age of plantations. In this study, we tested: i) if a single relationship can be used for all genotypes or if a genotype-specific relationship is necessary, both methods were compared using a parsimony criterion; ii) if genotypes can be grouped in several groups due to a given criteria, without excessive loss of precision to estimate LAI; iii) if different LAI-SVI relationships are needed for the different conditions of satellite acquisitions (solar position, geometry of acquisition); and iv) if the LAI-SVI relationships obtained from RTM provide good results on real acquired satellite images. The study site was located in Itatinga Municipality, in the state of São Paulo, southeastern Brazil. This area included a clonal test experiment with 16 different genotypes (treatments) obtained from different enterprises and regions of Brazil. Complete forest inventories were conducted for the plots and treatments at 6, 12, 19, 26, 38, 52, 62 months after planting. Leaves, soil and trunk optical properties were collected in 2010 and 2015 with ASD Field SpecPro and spectrometer. The Discrete Anisotropic Radiative Transfer Model (DART) was parameterized using leaf area (m^2), tree dimensions and locations data interpolated from field measurements. Simulations were made in nine dates comprising the period between 2010 and 2014. Seven different SVI's were analyzed, combined with 11 types of LAI - SVI regression models and 8 different possibilities of grouping the genotypes or the stand satellite acquisition variables. The best LAI x SVI relationships were chosen using the AIC and BIC criterion. The applicability of the relationship was evaluated using Worldview-2 images acquired in the three dates. The effect of using other satellite sensors was evaluated on their influence on LAI estimations. The NDVI was the SVI with the best estimations of LAI when it was used with a power function. The clone-specific relationship outperforms both global, stand and satellite conditions of acquisition. However, due to a poor simulation of the NIR1 band, a recalibration of the NIR1 band was necessary for better estimations of LAI using real acquired Worldview-2 satellite images. This shows limitations of LAI estimations based on RTM compared to calibration with *in situ* data. However, the work on RTM still allows to better understand the effect of the other biophysical parameters of the stand on SVI-LAI relationships as well as the effect of acquisition geometries.

Keywords: Leaf area index; Spectral vegetation index; Forest plantations; Remote sensing; 3D radiative transfer model; DART model

3.1 Introduction

The leaf area index (LAI) is a key biophysical parameter of forest plantations, related to several ecosystem processes, such as light interception, photosynthesis, water interception and transpiration, and biomass production. Its precise monitoring over time is essential to better understand the forest ecophysiological process. It can be critical for economic issues, including the trading of CO₂ quotas and the optimal balance between ecological preservation and forest exploration (HERNÁNDEZ et al., 2014).

Field measurements of LAI are normally performed using direct and indirect methods, such as allometric equations, destructive sampling and optical-based measurements (e.g. using hemispherical photographs and LAI-2000). Because field measurements are usually time-consuming, estimation of LAI using remote sensing products is an alternative to accurately retrieve this parameter over large areas and time. Several studies have reported the use of remote sensing techniques for LAI estimation for more than 30 years, and continue to be applied with different sensors and in different ecosystems (COLOMBO et al., 2003; le MAIRE et al., 2011; LEBOEUF et al., 2007). Many methods retrieve LAI from remote sensing images, which are separated between empirical methods and radiative transfer model (RTM). Empirical methods are mostly used, for instance, through the regression of LAI with spectral vegetation indices (SVI's) that are often computed through mathematical combinations of reflectance measured by sensors in the visible and infrared regions of the spectrum. Many studies have calibrated different SVI's for LAI estimations (DARVISHZADEH et al., 2008; le MAIRE et al., 2011; LIANG et al., 2015).

LAI estimations through radiative transfer model inversion (RTM) deals with the simulation of reflectance spectrum of forest landscapes from canopy and soil characteristics (KUUSK, 1995; LAURENT et al., 2011b), where these parameters are usually retrieved by inversion techniques. The tree-dimensional Discrete Anisotropic Radiative Transfer - DART - model (GASTELLU-ERCHÉGORRY et al., 1996) is an example of physically based RTM successfully tested on canopy reflectance measurements (GASTELLU-ERCHÉGORRY et al., 1999) and applied in several studies to relate reflectance to forest canopy characteristics (BANSKOTA et al., 2015; GUILLEVIC et al., 2013; MALENOVSKÝ et al., 2013).

Both SVI and RTM methods have advantages and drawbacks. For instance, SVI's can be sensitive to non-vegetation factors (e.g. soil background and sensor acquisition conditions) (OKIN et al., 2013) or other biophysical variables of the canopy that are not linked to LAI (leaf angle, leaf reflectance, etc.). RTM inversion techniques are based on the pre-requisite that the model gives results in a forward mode, which is not always the case, and are not

always tested, which could lead to uncertainties (JACQUEMOUD et al., 2009). These limitations can be overcome using a combination of these two methods, also called the hybrid method, which uses RTM to simulate spectral reflectance databases from field measurements followed by regression methods to determine the relationship between spectral and canopy parameters (JACQUEMOUD et al., 2009). Hybrid methods have the simplicity of the empirical methods and the robustness of RTM inversion methods and can bring a comprehensive link between SVI and estimated vegetation parameters, such as LAI (VERRELST et al., 2015). This approach could be used, for example, to test the effect of the species, background surface, tree parameters (e.g., leaf angle distribution and age), satellite and its images acquisition conditions (e.g. sun geometry and view angles) in the LAI - SVI relationship. Indeed, since the whole simulation database is generated, the process to combine, isolate and vary parameters is facilitated and could be applied in future approaches. Despite its potential, studies using the hybrid approach to retrieve forest biophysical parameters and evaluate the factor that directs its SVI's relationship are scarce.

This study used a hybrid method to investigate the possibility to estimate a relationship between SVI and LAI over a variety of genotypes and ages of eucalyptus forest plantations. The DART model was calibrated by extensive field measurements and used to simulate spectral reflectance of canopies. The calibration of this relationship was also analyzed by field measurements and Worldview-2 multispectral satellite images. In this study, we tested: i) if a single relationship can be used for all genotypes or if a genotype-specific relationship is necessary, both methods compared using a parsimony criterion; ii) if genotypes can be grouped in several groups based on a given criteria, without excessive loss of precision on LAI estimation; iii) if different LAI-SVI relationships are needed for the different conditions of satellite acquisitions (solar position, geometry of acquisition); and iv) if the LAI-SVI relationships obtained from RTM provide good results to real acquired satellite images.

This work is based on the hypothesis that accuracy of relationships between spectral vegetation indices and the leaf area index is improved when the hybrid method with SVI's and RTM is used to account for stand properties and effects of satellite acquisition conditions.

3.2 Material and Methods

3.2.1 Study Site

The study site was located in Itatinga Municipality, in the state of São Paulo, southeastern Brazil, 22°58'04''S and 48°43'40''W. In the last 15 years, average annual rainfall was about 1391 mm, with 75% of this total concentrated between October and March (CAMPOE et al., 2013). The average annual temperature from January 2010 to December 2012 was 19.3°C, ranging from 16.3°C (June to August) to 22.2°C (December to February). The average annual relative humidity was 75%, with minimum values observed between June and September ($\approx 30\%$). The slope was lower than 5% and the maximum area elevation was 760 m above sea level (DA SILVA et al., 2011). Soils are very deep oxisols in the upper part of the study site (750 m above sea level) with low clay content ($\approx 20\%$) and at the lowest elevation (725 m above sea level) with high clay content ($\approx 40\%$).

In this study, we analyzed a clonal test experiment that was planted in November 2009 and included 16 different genotypes (treatments), comprising several genetic origins from different enterprises and regions in Brazil (Table 1), 14 of these treatments were clonal and two were seminal materials. The clonal test was designed to evaluate the genetic variability effect of currently cultivated genotypes on productivity (IPEF, 2012).

Table 1 - Description of the 16 treatments used in the clonal test

Treatment	Description	Name
1	<i>E. grandis</i> seeds CH Duratex	SEM01
2	<i>E. grandis</i> seeds monoprogeny Duratex	MON02
3	<i>E. grandis</i> Clone Eucflux	EUC03
4	<i>E. grandis</i> x <i>urophylla</i> Clone Duratex	DUR04
5	<i>E. grandis</i> x <i>urophylla</i> Clone Fibria	FIB05
6	<i>E. grandis</i> x <i>urophylla</i> Clone Fibria	FIB06
7	<i>E. grandis</i> x <i>urophylla</i> Clone V&M Tubes	VMT07
8	<i>E. grandis</i> x <i>urophylla</i> Clone Cenibra	CEN08
9	<i>E. grandis</i> x <i>urophylla</i> Clone Copener - Humid area	COP09
10	<i>E. grandis</i> Clone Conpacel	CON10
11	<i>E. grandis</i> x <i>urophylla</i> Clone Suzano - High productivity	SUZ11
12	<i>E. grandis</i> x <i>urophylla</i> Clone ArcelorMittal BioEnergia	AMB12
13	<i>E. grandis</i> x <i>urophylla</i> Clone ArcelorMittal BioEnergia	AMB13
14	<i>E. saligna</i> Clone Klabin	KLA14
15	<i>E. grandis</i> x <i>urophylla</i> Clone Suzano - Medium productivity	SUZ15
16	<i>E. camaldulensis</i> x <i>grandis</i> Clone Copener - Dry area	COP16

The clonal test comprised 10 blocks distributed within 200 Ha of an industrial stand managed by Duratex Company, each block with 16 treatments (16 different genotypes) randomly distributed in a 4 x 4 subplot matrix. Each treatment had 12 rows of 16 trees, planted at 3 x 2 m, totalizing 192 trees per plot. Only 100 trees located in the central part of the plot (20 x 30 m) were analyzed and the other trees were considered as border trees. Figure 1 shows

the location of the clonal test blocks (different colors) and plots with the treatments (rectangles) with different north orientations.

Figure 1 - Location of study site with the clonal test experiment. Filled rectangles are representative of the plots with the treatments (16 genotypes) inside the blocks (represented by different colors). The arrow indicates the trend of increase in soil clay content from ≈ 20 to $\approx 40\%$ across the site

3.2.2 *In-situ* measurements of LAI and other stand biophysical properties

Complete forest inventories of all blocks and treatments were carried out for the treatments at 6, 12, 19, 26, 38, 52, 62 and 73 months after planting. During these surveys, trunk circumference at breast height (CBH) was measured, with occasional measurements of tree height. In each of these dates, 10 to 12 trees of different sizes were cut for each genotype,

within the border trees of blocks 2, 3 and 10. These destructive measurements were used to calibrate allometric relationships between CBH and tree height, between CBH and canopy height, CBH and crown diameter in the planting line and inter-row directions, CBH and tree total leaf area, CBH and the biomass of different tree components (leaves, branches, bark and stem wood), as in the study of Laclau et al., (2008). The leaf area index was computed for each treatment and blocks as the sum of the total leaf area of 100 trees divided by the area of this subplot. At the end, $16 \times 10 = 160$ LAI values were computed in each date of the inventory.

Leaves, trunk and litter optical properties were extracted with ASD Field SpecPro (Analytical Spectral Devices, Boulder, Colorado, USA) spectrometer within the spectral range from 300 to 2500 nm at 71 months after planting, in October 2015. Leaf optical properties comprehended the reflectance and transmittance collected using a LiCor integrating sphere. We selected three trees per treatment (genotypes) and for each tree, leaves were collected at three crown layers (bottom, middle and top) and two horizontal positions in each layer, totaling two leaves per crown layer, six leaves per tree and 18 leaves per treatment. Litter and trunk optical properties comprehended the reflectance. Litter and trunk reflectance were collected for each treatment (genotypes) in three different locations in the field to generate one composite sample per treatment to be measured in the laboratory using a Contact Probe in five different points of the composite sample.

Leaf Angle Distribution (LAD) was computed from the leaf angle orientation measured in the field in six felled trees for each genotype. In each tree, the inclination of 72 leaves was measured with a clinometer. These 72 leaves were selected according to their position in the crown: three different crown heights, four auxiliary branches at each height (two in row planting and two in inter-row planting), and six leaves along the length of these auxiliary branches.

We analyzed tree growth in nine distinct dates from 2010 to 2014, when the stands were four (March 2010), 10 (Sept. 2010), 16 (March 2011), 22 (Sept. 2011), 28 (March 2012), 34 (Sept. 2012), 40 (March 2013), 46 (Sept. 2013) and 52 (March 2014) months of age. The main characteristics of the trees for each age for all genotypes analyzed are shown in Figure 2.

Figure 2 - Average values of the tree characteristics of each treatment (genotypes, labeled G1 to G16) at each age. (a) Diameter at Breast Height -DBH (cm), (b) total tree height (m), (c) crown diameter (m), (d) number of stems and (e) leaf area (m²)

3.2.3 Worldview-2 images and creation of the experimental dataset

Three Worldview-2 multispectral satellite images were acquired in the study site and their configuration is described in Table 2. The Worldview-2 images were acquired in three dates (May 2010; Aug. 2010; and July 2013), corresponding to different trees developing stages, respectively, at six, nine and 44 months of age. The characteristics of Worldview-2 images were given in section 2.2.6 of Chapter 2. The BOA reflectance was computed following atmospheric corrections obtained in the chapter before. This BOA reflectance was

used to prepare the experimental dataset (empirical approach), which includes the associated *in situ* LAI measurements.

Table 2 - Main acquisition parameters of Worlview-2

Date of acquisition	Acquisition time (GMT)	Sensor azimuth angle (°)	Sensor elevation angle (°)	Sun azimuth angle (°)	Sun elevation angle (°)
May, 2010	13:29	53.5	70.7	33.5	68.1
August, 2010	13:43	297.7	83.2	32.5	42.7
July, 2013	13:29	319.9	62.8	24.0	40.6

3.2.4 The 3D DART radiative transfer model

The Discrete Anisotropic Radiative Transfer (DART) is a comprehensive model that can be used for the retrieval of physically based canopy parameter. DART simulates radiative transfer in heterogeneous 3D landscapes with the exact kernel and discrete ordinate methods (GASTELLU-ETCHEGORRY et al., 2004). Any landscape is simulated as a rectangular matrix of parallelepiped cells. Radiation propagates in a finite number of directions with an angular sector width (steradian). Incident Irradiance in the scene has the direct sun and atmospheric source vectors. They are assumed to originate from a fictitious cell layer at the top of the scene and the atmospheric (diffuse) source vectors implies the use of a coupled atmospheric mode. More detailed information about DART physical components can be found in CESBIO, (2013a, 2013b, 2013c) and GASTELLU-ETCHEGORRY et al. (2004). DART uses information from spectral intervals - or spectral bands - with mean optical properties of the simulated objects. Output options include computation of images at the bottom (BOA) and top of atmosphere (TOA) on several geometries of acquisition and radiative budget products, among others.

The simulations of vegetation landscapes require, besides the definition of the spectral bands and their computation methods, input parameters related to the structural characteristics of trees (tree position and dimensions, LAI, LAD, etc.). The optical properties of the scene comprise the sun position, view angle, position and structural characteristics of objects, scene dimensions and cell size.

3.2.5 Creation of a reflectance simulation dataset from the DART model

In this study, the flux tracking method in the reflectance mode ('R') was used to simulate reflectance on 21 spectral intervals with amplitudes ranging from 20, 30 and 40 nm

in the visible and near infrared region (360 to 1100 nm) to cover the main region of the canopy reflectance analysis. The ellipsoidal distribution function of leaf angle was used, which requires the average leaf angle (ALA) as an input parameter. This value was computed from the leaf angle orientation measured in field campaigns. LAI was calculated from field measurements (computed from allometric relationships as shown in Chapter 2 Section 2.2.2), for each tree. The input solar zenith and azimuth angles (respectively, θ_s and ϕ_s) were obtained from the sun position computation from the local latitude ($22^\circ 58' 04''$ S) and exact time of the year, for the simulated dates. In the present study, we created a dataset of simulations for March/2010, Sept/2010, March/2011, Sept/2011, March/2012, Sept/2012, March/2013, Sept/2013 and March/2014, each at 10:30 a.m. We simulated 78 view angles at each date, varying from 0° to 30° (5° intervals) for zenith (θ_v) and 0° to 360° (30° intervals) for azimuth (ϕ_v). We used these view angles to evaluate the effect of geometry acquisition on vegetation indices. Simulations were performed using the exact tree position and dimensions of 100 central trees, for each genotype, block and date, totaling 1440 plot-scale simulations (16 genotypes, 10 blocks and 9 dates) with scene size 600 m^2 ($20 \times 30 \text{ m}$) and cell size ($\Delta x = \Delta y = \Delta z$) 0.25 m .

The model output analyzed in this study was the mean reflectance of the plot at the bottom of atmosphere (BOA). The BOA mean reflectance of 21 simulated bands was convolved to eight multispectral band of Worldview-2 satellite, using the relative response spectra of the sensor. Also, as in le Maire et al. (2011), an additional random error ($\mu = 0, \sigma^2 = 0.03$) was added to the DART simulated reflectance to represent spectral noise inherent to sensor measurement.

The simulated dataset included, at the end, the simulation of eight BOA reflectance images for eight bands of Worldview-2, in nine dates, 10 blocks, 16 genotypes and 78 view angle configurations. The simulations were made in a cluster of computers run during ~3 days.

3.2.6 Spectral vegetation indices and regressions with LAI

Spectral vegetation indices (SVI) are mathematical combinations of the reflectance in different spectral bands, which could be quantitatively correlated with some biophysical characteristics of vegetation, such as LAI. Its calculation is simple, based on the reflectance measured by the sensor, and no information about satellite acquisition and sun geometries is required (le MAIRE et al., 2012). In this study, we focused on vegetation indices used to predict LAI. We aimed to identify which index better explains LAI in *Eucalyptus* plantations,

using mainly the red and the near infrared bands. The indices tested include the Normalized Difference Vegetation Index - NDVI (ROUSE et al., 1973), the Enhanced Vegetation Index - EVI (WANG et al., 2002), the modified Enhanced Vegetation Index - EVI2 (JIANG et al., 2008), the Soil Adjusted Vegetation Index - SAVI (HUETE, 1988), the Optimized Soil Adjusted Vegetation Index - OSAVI (RONDEAUX et al., 1996) and the Generalized Soil Adjusted Vegetation Index - GESAVI (GILABERT et al., 2002) and the '*Eucalyptus*' Vegetation Index - EucVI calibrated for *Eucalyptus* plantations (le MAIRE et al., 2012). The formulations of these parameters are reported in Table 3.

Table 3 - Summary of the analyzed vegetation indices, equations and used parameters

Equation	SVI	Parameters						
		a	b	c	d	e	f	g
$SVI = g \frac{aNIR + bRED + c}{dNIR + eRED + f}$	NDVI	1	-1	0	1	1	0	1
	EVI ⁽¹⁾	1	-1	0	1	C_1	$C_2 Blue + L$	G
	EVI2 ⁽²⁾	G	$-G$	0	1	$6 - 7.5/C$	1	1
	SAVI ⁽³⁾	$(1 + L)$	$-(1 + L)$	0	1	1	L	1
	OSAVI ⁽⁴⁾	1	-1	0	1	1	Y	1
	GESAVI ⁽⁵⁾	1	$-A$	$-B$	0	1	Z	1
	EucVI ⁽⁶⁾	1	-1.881	0.001	0.094	1.407	0.018	1

(1) L is a soil adjusted factor and the parameters C_1 and C_2 describe the blue band usage for the correction of the red band; the parameters are empirically determined by standard values, respectively, 1, 6 and 7.5; G is a gain adjusted factor, with standard value 2.5; $Blue$ is the mean reflectance of the blue band (450-510 nm). (2) C is a parameter as in $RED = C \times Blue$, with the standard value 2.08; G is a gain adjusted factor, with the standard value 2.5. (3) L is a factor of adjust for the canopy substrate with the standard value 0.5. (4) Y is a soil adjustment parameter with the standard value 0.16. (5) A is the slope and B is the intercept of the soil line ($NIR = B + A \times RED$), adjusted values were, respectively, -1.6 and -0.019; Z is a parameter with standard value 0.35. (6) Parameters a and g were fixed at 1 and the others were adjusted a *Eucalyptus* plantation database described in le Maire et al. (2012).

Since LAI estimation using these SVI shows different relationships, linear or non-linear, 15 regression models were tested, which used 1 to 3 parameters (Table 4).

Table 4- Models used to calibrate SVI x LAI

Model number	Function family	Description	N° Parameters
1	Linear	$LAI = \beta_0 + \beta_1 SVI + \varepsilon$	2
2	Linear	$LAI = \beta_1 SVI + \varepsilon$	1
3	Logarithmic	$LAI = \beta_0 / \ln SVI + \varepsilon$	1
4	Logarithmic	$LAI = \beta_0 + \beta_1 / \ln SVI + \varepsilon$	2
5	Logarithmic	$LAI = \beta_0 + \beta_1 / R(\beta_3 \ln SVI) + \varepsilon$	3
6	Logarithmic	$LAI = \beta_0 + \beta_1 SVI / \ln SVI + \varepsilon$	2
7	Logarithmic	$LAI = \beta_0 + \beta_1 SVI / R(\beta_3 \ln SVI) + \varepsilon$	3
8	Logarithmic	$LAI = \beta_0 + \beta_1 \ln SVI + \varepsilon$	2
9	Logarithmic	$LAI = \beta_0 + \beta_1 SVI R(\beta_3 \ln SVI) + \varepsilon$	3
10	Power	$LAI = \beta_0 SVI^{\beta_1} + \varepsilon$	2
11	Power	$LAI = \beta_0 SVI^{\beta_1} + \beta_2 + \varepsilon$	3
12	Power	$LAI = \beta_0^{\beta_1 SVI} + \varepsilon$	2
13	Power	$LAI = \beta_0^{\beta_1 SVI + \beta_2} + \varepsilon$	3
14	Exponential	$LAI = \beta_0 e^{\beta_1 SVI} + \varepsilon$	2
15	Exponential	$LAI = \beta_0 e^{\beta_1 SVI + \beta_2} + \varepsilon$	3

First, a model adjustment based only on the experimental dataset (*in situ* LAI measurements and satellite images reflectance) was performed. Then, we used the simulation dataset described above to calibrate relationships between DART-simulated SVIs and LAI. Both approaches were compared afterward. In the case of simulation dataset, the LAI used to adjust these models was the one effectively used in DART simulation in the sub-plot (could be slightly different from *in situ* simulation, see Chapter 2 Section 2.3.3). SVI's were computed using the blue (450-510 nm, for EVI), red (630-690 nm) and NIR1 (770-785 nm) convolved bands (using the relative spectral response of Worldview-2) from the DART simulations for each genotype, block, view directions and ages. In the first chapter, we found a problem for simulations of the near infrared band (NIR1). However, since it was a systematic problem (see chapter 1), we considered that it did not affect the SVI - LAI relationships performance and analysis, but only the quantitative estimates of LAI. To fix this problem, we applied a direct correction of the simulated NIR1 reflectance based on the Worldview-2 image reflectance.

3.2.6 Statistical analysis

Some intrinsic stand properties, sun and view zenith and azimuth angles were analyzed to better understand their influence on the relationship between spectral vegetation and leaf area indices and, consequently, the number of parameters and model calibration requirements. For both experimental and simulation reflectance datasets, the analyzed stand, sun and satellite characteristics were arranged in groups, and the calibration of the SVI - LAI models (described in Section 3.2.6) was made for each group.

For the experimental dataset, we tested three different groups: 1) all genotypes, which represented a global adjustment for all characteristics (no group); 2) each genotype separately, which should logically lead to a better individual modelling performance, but at the expense of the total number of parameters (16x1 to 16x3 parameters depending on the equations); 3) age groups, where one regression was performed in each image.

For the simulation dataset, nine groups of parameters were analyzed, which were: 1) all genotypes together; 2) each genotype separately; 3) four groups of genotypes according to the mean soil reflectance collected in field measurements and grouped after the clustering analysis; 4) four groups of genotypes according to the mean leaf reflectance collected in field measurements and grouped after the clustering analysis; 5) two groups for the view zenith angles (5° to 15° and 20° to 30°); 6) two groups for the view azimuth angles relative to the east-west and north-south raw orientations; 7) four groups for the average leaf angle values

grouped by 25, 50 and 75% quartiles; 8) four groups for the sun zenith angles relative to the blocks raw orientation grouped by 25, 50 and 75% quartiles; and 9) four groups for the sun azimuth angles relative to the blocks raw orientation grouped by 25, 50 and 75% quartiles.

The SVI - LAI models were compared by means of their r-square (R^2), root mean square error (RMSE), Akaike Information Criterion (AIC) (AKAIKE, 1973) and Bayesian Information Criterion (BIC) (SCHWARZ, 1978). AIC and BIC criteria were the most important, because they can compensate a result performance by the number of parameters in the model. We can show the advantage of such criteria with an example on two extreme cases, the global model and the genotype-scale models: clearly, local adjustments for each genotype will give better results than a unique regression for all clones, simply because the number of parameters of the model increases. For instance, for a linear regression, only two parameters are calibrated in the global adjustment, while $2 \times 16 = 32$ parameters are calibrated in the genotype-scale case. Indeed, performance of an adjusted model depends largely on the number of free parameters (effective dimension) of the model (ATKINSON et al., 2012). AIC and BIC criteria compensate for this effect of numbers of parameters and allow to compare the performance of models having different number of parameters, for the same dataset, using a parsimony criterion. The AIC can be used to measure the effective performance of a model with a penalization of models having a large number of parameters. A lower value of AIC indicates that the model is preferable. AIC is calculated using Equation 1:

$$AIC = 2k + n(\ln RSS) \quad (1)$$

Where, k is the number of free parameters in the model, n is the number of input data and RSS is the residual sum of squares between the original data and fitted model.

The Bayesian Information Criterion (BIC) is another measurement of the goodness of fit, similar to AIC, but using a Bayesian framework and also adjusted for the sample size. It generally penalizes free parameters more strongly than AIC does. It is calculated using Equation 2:

$$BIC = n(\ln \hat{\sigma}^2) + k \ln n \quad (2)$$

Where $\hat{\sigma}^2$ is the error variance and k is the number of free parameters in the model n is the number of input data, similar to that in the AIC.

We compared together the sets of regressions (all combinations of SVI's with all types of regression models) obtained with the nine grouping possibilities using the AIC and BIC criteria. Lower AIC (or BIC) for one of the grouping possibilities would mean a better model, taking into account the parsimony rules. This method was applied to both the experimental and the simulation dataset.

Finally, to evaluate the different best models obtained (either in the experimental or simulation dataset), we applied the regression to the Worldview-2 reflectance. In the case of the calibration on experimental dataset, it was not a perfect validation since the data are not independent. In the case of the regression, however, the validation is therefore made in the independent dataset. This final comparison between measured and estimated LAI was described in terms of RMSE.

3.3 Results

3.3.1 LAI - SVI calibrations in the experimental dataset

The general behavior of calibration of SVIs with the experimental dataset and with a global adjustment curve is shown in Figure 3 for six SVI's using the RED and NIR1 bands. For each model and SVI, the AIC criterion was presented in Table 5. Here and in the rest of this study; we focused on AIC, because BIC provided very similar results. In Figure 3, only the best regression model was represented (dark line), corresponding to the model with the lowest AIC in the Table 5. The best model adjustment was obtained for model 11 (power function) with the NDVI ($R^2=0.93$ and $RMSE=0.51$), followed by the GESAVI.

Figure 3 - LAI estimated by the Spectral Vegetation Indices using a global adjust for three dates (May 2010, August 2010 and July 2013). Dart line (regression) represents the best-adjusted model

Table 5 - AIC values for the 6 SVI's using a global adjustment

Model	Spectral Vegetation Index					
	NDVI	EVI2	SAVI	OSAVI	GESAVI	EucVI
1	1200.1	1140.7	1167.7	1159.7	831.5	1122.8
2	1657.2	1474.1	1552.7	1601.9	840.2	1179.6
3	797.5	1168.7	1309.6	1313.3	2403.1	1535.3
4	790.2	1072.3	1027.6	926.4	1990.0	1128.9
5	773.0	1048.0	1028.1	884.7	1989.8	1054.1
6	791.8	1087.8	1016.5	893.9	1986.8	1025.4
7	767.1	1035.7	1017.6	991.9	1986.1	1024.7
8	944.8	1156.7	1136.3	915.9	800.7	1415.5
9	840.0	1013.6	998.1	885.9	799.7	1010.3
10	861.2	1032.3	1019.5	912.3	841.3	1050.8
11	736.5	1020.4	997.2	840.5	803.7	1011.3
12	1660.2	1481.1	1554.4	1602.0	974.9	1234.5
13	993.1	1038.8	1040.1	978.2	889.4	1029.6
14	799.2	1036.6	1006.0	863.4	915.3	1041.3
15	739.5	1031.8	1007.8	850.1	817.4	1028.2
16	1200.1	1140.7	1167.7	1159.7	831.5	1122.8

We tested two other options of grouping the variables for the regression, one consisting of a different calibration for each genotype and the other consisting of an adjustment for each image (different ages). AIC values of the models with the best adjustment for each SVI and types of grouping are shown in Figure 4. In this figure, we observe, as mentioned above, that the NDVI adjusted by model 11 was the best SVI for the global adjustment. When we analyze the grouping of variables represented by the age, the SVI performance changed and the EucVI was the best SVI adjusted with model 10 (also a power function). However, the best SVI results based on the most parsimonious regression (lower AIC and BIC) was achieved by the adjustment of each genotype, using the NDVI and model 11 (Table 6).

Figure 4 underlines the best effect of individual characteristics of the genotypes to determine LAI - NDVI relationships. The analysis of grouping variables in the adjustments shows an increasing improvement of the relationship from the global to the individual genotype calibration. We also show that the use of a different relationship for each image does not bring systematically a better regression, but this analysis is limited because the different images are taken at different ages (therefore LAI ranges), thus, both effects (image and age) are not dissociable. In the next section, we will check if these results are corroborated by the RTM simulations, and we will investigate further the analyses of grouping variables possibilities.

Figure 4 - Minimum AIC values for all SVI's per stand properties groups. Numbers in the group point lines represent the calibrated model that shows the best fit

Table 6- Parameters of the best-adjusted model for the NDVI - LAI relationship on experimental dataset

Model attributes	Clone	Parameter		
		β_0	β_1	β_2
	1	71.7809	2.1596	0.5042
	2	55.9748	2.0142	0.8197
Type	3	40.1188	1.7778	0.1776
Power (Model 11)	4	195.7899	3.0911	0.8372
	5	87.9718	2.3681	0.5030
	6	41.8949	1.7567	0.5220
	7	72.3971	2.2761	0.5853
Description	8	234.1655	3.1476	0.9288
$LAI = \beta_0 SVI^{\beta_1} + \beta_2 + \varepsilon$	9	133.8030	2.6631	0.7133
	10	170.9877	2.7458	0.8669
	11	39.2634	1.6829	0.5283
	12	45.5247	1.9727	0.5050
R ²	13	62.1124	2.0456	0.6112
RMSE	14	63.2813	2.0494	0.4688
	15	48.3140	1.9625	0.3157
	16	35.8238	1.7163	0.3039

3.3.2 LAI - SVI calibrations on simulation dataset

A great variety of AIC and BIC was obtained depending on the chosen SVI, regression model and grouping of the genotypes. The AIC and BIC values were very similar, therefore, only AIC was presented (Figure 5). The best model, based on a parsimony rule, showed the lowest AIC values. The SVI with the lowest AIC values were NDVI, followed by EucVI and GESAVI. The SVI with the worst results was SAVI, followed by EVI2.

The best regression model changed between SVI's, but with predominance of the non-linear regression models 9 and 11 (Table 4), the former is a logarithmic function and the latter, a power function. For NDVI, the regression model 7 showed the minimum values of AIC, but the results were very close to those in model 11 with AIC equal to 0.45066×10^{-5} . Both models showed realism in terms of the SVI x LAI scattering behavior, but with a better behavior and simplicity for model 11, which was further kept.

The best group for all the SVI's was the adjustment for each genotype, the same of the experimental dataset. In this case, even if the total number of parameters to be adjusted was large (32 for a 2-parameter regression model) the gain in terms of precision would be even higher. The second best way of grouping the genotypes was the grouping based on leaf optical properties (reflectance). In this case, the best SVI's were GESAVI and OSAVI. Another grouping possibility that worked well was the grouping of genotypes based on their litter reflectance, and, in this case, NDVI, EucVI and SAVI performed best. The other groups did not show great improvements in terms of AIC and BIC values compared to the global adjustment (no group, single regression for all clones). Average leaf angle (ALA), sun and view zenith and azimuth angles did not influence much the regression calibration, with similar results to those observed for overall regression. Similar to the experimental dataset, regardless of the types of grouping and regression models, the best SVI ordering of was NDVI, EucVI and GESAVI, OSAVI, EVI, EVI2 and SAVI.

If one model had to be kept, our results showed that it would be one single model for each clone, based on NDVI and regression model 11 (Table 4). In this case, the overall R^2 and RMSE of the calibration were equal to 0.97 and 0.29, respectively (Table 7). Table 7 also presented the adjusted parameters for each genotype, all significant at 95% confidence level.

Figure 5 - Minimum AIC values for all SVI's per property groups of stands. Numbers in the group of point lines represent the model that showed the best fit. The 'x' label is an abbreviation of the group names, such as: No group = all clones, Genotypes = each genotype, Litter = mean litter reflectance, Leaf = mean leaf reflectance, View Zen = view zenith angles, View Azi = view azimuth angles, ALA = average leaf angle, Sun Zen = sun zenith angles and Sun Azi = sun azimuth angles

Table 7 - Parameters of the best-adjusted model for the NDVI x LAI relationship

Model attributes		Clone	Parameter		
			β_0	β_1	β_2
Type	1	9.8299	1.8241	-0.4382	
	2	10.1468	1.7081	-0.1391	
	3	8.7999	1.5365	-0.2548	
	4	9.4095	2.0485	0.0997	
Power (Model 11)	5	7.6241	1.8334	0.3957	
	6	11.4211	2.3813	0.5292	
	7	8.6029	2.0138	0.3690	
Description	8	9.2016	2.2045	0.3849	
	9	9.2667	1.9324	0.3143	
$LAI = \beta_0 SVI^{\beta_1} + \beta_2 + \varepsilon$	10	11.3694	2.0211	0.5112	
	11	9.5033	1.9644	0.3796	
	12	9.4357	1.9894	-0.2857	
R^2	RMSE	13	9.6844	1.6246	-0.0243
		14	9.0507	1.5770	-0.1765
0.97	0.29	15	8.7454	1.9173	-0.2756
		16	7.3550	1.1451	-0.5410

Figure 6 shows the selected NDVI - LAI regressions obtained from DART simulations for each genotype in all blocks and dates as well as for a single view direction angle ($\theta_v = 15^\circ$, $\varphi_v = 30^\circ$). The simulated NDVI values were between 0.2 and ≈ 0.8 for LAI values between near zero and $\approx 7.5 \text{ m}^2/\text{m}^2$. An overall analysis showed greater sensitivity of NDVI for smaller LAI, where small differences in NDVI lead to higher variation in LAI values. These simulations show that each genotype had a well-defined NDVI - LAI curve, and changing from one curve to the other (e.g. applying a regression calibrated for one

genotype to another genotype) can lead to significant errors (greater than 20% error). In other words, for the same NDVI value, true LAI can vary between genotypes. Genotype 10 presented, in general, higher LAI values compared to the other clones for a given NDVI. Conversely, clones 12 and 15 presented the lowest LAI values for a given NDVI.

Figure 6 - Calibrated NDVI and estimated LAI from DART simulations by adjusted model 7 for each genotype group (16), all blocks (10) and simulated dates (9); and one view direction angle ($\theta_v = 15^\circ$, $\phi_v = 30^\circ$). Numbers inside the figure for each curve represent the respective genotype number to support the legend identification (G1 to G16)

Figure 7 represents the calibration results, that is, the relationship between the LAI used as input in the DART simulation dataset compared to the LAI obtained from the reflectance of the DART simulation dataset, using the genotype-specific regressions presented in Table 5. This figure confirms the good regression statistics of the model calibration step ($R = 0.97$).

Figure 7 - LAI of the DART simulation dataset and LAI estimated from the DART simulation dataset (reflectance) by model 11 and NDVI for all clones, blocks and dates; and one view direction angle ($\theta_v = 15^\circ$, $\varphi_v = 30^\circ$)

3.3.3 Comparison of the experimental and simulation results

In the sections presented above, we observed that the experimental and simulation dataset obtained similar results for regressions between SVI and LAI. The best models were obtained, in both cases, for a genotype-specific regression, a simple NDVI index with a regression model with nonlinear power function. The RTM modeling part allowed to confirm that the genotype specific regressions are not attributed only to a particularity of the experimental dataset. Indeed, the RTM dataset was built for more ages, sun angles, and view conditions than the only three images that were used first. We also confirmed that other satellites with other Relative Response Spectra could have obtained the same results (not shown here). We can therefore rely on the fact that NDVI and power functions, applied at the genotype scale, provides a better overall result than the other groups or a single regression.

The next step, as underlined in the introduction, is to try to use the regression obtained from the RTM simulation dataset directly on measured reflectance. The idea is that this regression, obtained from RTM, could easily be obtained from different satellite and view configuration, and therefore would not require field measurements for each satellite measurement. The direct use of RTM derived regression (similar to a model inversion),

requires the prior accuracy of the model in the forward mode. We observed in Chapter 1 that accuracy is correct for most bands, except for the NIR1 band. This is shown in Figure 8 below, on a scatter plot with NIR - RED reflectance. It clearly shows that, while RED simulated values are within the range of measurements, NIR simulated values are clearly underestimated.

Figure 8 - NIR vs. RED reflectance of the experimental dataset (red) and simulation dataset (blue). Dark blue points represent nadir-viewing configuration

The NIR1 band is used to compute most SVIs. Therefore, there is a large discrepancy between the SVI of the simulated and the experimental dataset (Figure 9). We can see in Figure 9 that while most indices remain within the range of simulations, they are generally located on the extreme part of the simulation range, opposite to the nadir-viewing configuration. We can therefore conclude that underestimation of NIR band leads to an underestimation of SVI and that the regression calibrated in RTM will not be usable directly in the experimental dataset.

Figure 9 - SVI's in relation to LAI for the experimental dataset (red) or simulation dataset (blue). Dark blue points represent nadir-viewing configuration

3.3.4 Application of the vegetation indices to satellite images

When the regression model obtained previously (one equation per genotype) to the simulation dataset were applied to the NDVI values obtained from the satellite Worldview-2 images, acquired in May 2010, Aug. 2010 and July 2013, the result showed a clear overestimation of the predicted LAI (Figure 10a), for all dates and clones. As underlined in the previous section, this is attributed to the underestimation of the simulated NIR1 band used in DART, leading to an underestimation of DART NDVI compared to the measured WorldView-2 NDVI, which finally leads to an overestimation of the predicted LAI.

A post-processing technique was applied through NDVI - LAI re-calibration using the satellite red (630-690 nm) and NIR1 (770-785 nm) bands. A simple re-calibration of the simulated NIR1 band, based on a linear regression between NIR1 obtained from Worldview-2 and NIR1 simulated in the three dates (Chapter 1) was performed in order to estimate the prediction error of the method and ensure the NIR1 band had not shown any bias. Since the NDVI changed after this correction, it was necessary to change the regression parameters accordingly (Table 8). The comparison between LAI estimated from NDVI after the NIR1

correction and LAI obtained from field measurements is shown in Figure 10b, and obtained R^2 and RMSE 0.96 and 0.39, respectively (Table 8).

Figure 10 - Comparison of observed LAI (measured in the field) and estimated LAI from NDVI using the same parameters adjusted for model 11 and each genotype group using the images simulated by DART in nine different dates (a); and the same comparison but using a re-calibration of this model using Worldview-2 satellite images (b). These results present all genotypes and blocks for the dates May 2010 (plus sign symbol), August 2010 (point symbol) and July 2013 (diamond symbol)

Table 8 - Parameters of the best model (NDVI) for the new adjustment

Model attributes	Clone	Parameter		
		β_0	β_1	β_2
Type	1	9.2080	8.6410	0.6847
	2	6.1059	4.6716	0.7784
	3	8.1830	6.7864	0.4954
	4	8.3476	7.0493	0.7844
Power (Model 11)	5	9.6245	8.4039	0.6114
	6	8.1245	5.4266	0.6968
	7	7.1285	7.1144	0.7529
Description	8	9.6061	10.0181	1.0617
	9	10.7069	8.6214	0.7922
	10	10.1275	6.0248	0.7791
$LAI = \beta_0 SVI^{\beta_1} + \beta_2 + \varepsilon$	11	11.6280	9.0146	1.0129
	12	8.5847	8.0221	0.7662
	13	8.8514	6.9111	0.7991
R^2	14	7.0858	6.0581	0.5742
	15	7.2813	5.8908	0.4083
	16	6.6686	6.4214	0.5382
RMSE				
0.96		0.39		

The comparison between the LAI estimated from the NDVI simulated for Worldview-2 image and the LAI estimated from NDVI simulated for other satellites such as Quickbird, Landsat5 TM and IKONOS2 is shown in Figure 11. Besides the high correlation ($R = 0.99$), we can observe the influence of the sensor type on the LAI estimated with variations in the curve inclinations and meaning that LAI-NDVI relationship should be re-

calibrated for each satellite. An error of one point of LAI can be caused by these differences in the satellite spectral responses.

Figure 11 - Comparison between estimated LAI for Worldview-2 satellite and other three satellites (plus sign symbol for Quickbird, cross symbol for Landsat5 TM and square for IKONOS2) for all genotypes and dates and one view direction angle ($\theta_v = 15^\circ$, $\varphi_v = 30^\circ$). Both LAI were computed from the convolution of bands simulated by DART

3.4 Discussion

The first part of the results presented the calibration of LAI - SVI relationships based only on *in-situ* LAI measurements and SVI from real satellite images. The NDVI using a model with two parameters and the grouping calibration for each genotype showed the best relationship. These regressions, obtained from a large range of genotypes, can therefore be used further for application purposes. However, they were obtained from a single sensor, from a given satellite configuration, and only from three ages, thus, their generality remains questionable (which is the main drawbacks of experimentally-calibrated regressions). Also, the use of these experimental datasets did not allow concluding if this grouping per genotype had a biophysical origin or if there was other ways of grouping that could provide similar or better results. In fact, it also reinforces some important questions about the experimental approach: What if we do not have an experimental dataset to calibrate the relationship? What if the dataset does not correspond to the time of satellite overpass? What if the satellite

images do not have adequate spatial resolution to analyze this type of very small plots? We therefore attempted to answer these questions by using DART RTM modelling.

The RTM gives a physical basis of the relationship between reflectance and LAI, and between reflectance and other variables, which can help to understand why the genotypes should be grouped or not. Moreover, once DART was parameterized for different ages of the eucalyptus stand, it allowed the calibration of any type of SVI and LAI values for any satellite type (e.g., different sensors and spectral resolutions) and at any measurement date and sun configuration. However, it means that the model must simulate correctly the SVI. In our case, the study has shown limitations in the SVI from DART simulations to achieve the SVI values of Worldview-2. These models are traditionally difficult to validate and problems in simulating wavelengths can be found as part of the modeling uncertainties. The Radiative transfer Model Intercomparison (RAMI) exercise focuses on the benchmarking of these types of models and difficulties to describe complex canopy structures have been reported by users (WIDLOWSK, 2015). In the RAMI exercise, a good performance was reported for the DART model. The discrepancies that we found between simulated and satellite SVI values was due to the unsolved problem of simulation in the NIR1 band, which had to be corrected afterward. This problem did not appear in the RAMI intercomparison, and we therefore expect that the problem of NIR1 reflectance underestimation does not come from an internal problem of the DART model, but from error in the model parameterization. Another study on different RTM model has shown that such discrepancies between modeled reflectance and simulated reflectance often occur (ATZBERGER et al., 2013) and are dealt differently each time. Sometimes, the poorly simulated band is discarded, sometimes it is corrected, and sometimes more uncertainty is added to the simulation of the band. One alternative to this issue could be the use of learning machine techniques in the simulated dataset to explore other bands besides the NIR1 to retrieve the LAI that better explains this parameter. While a simple correction of NIR1 was made in this work, we underline that it is not the most adequate proceeding, and a better understanding of the reasons of this issue need to be identified. However, since this problem causes a systematic error to the database, it did not necessarily affect the analysis of LAI - SVI relationship, and a better understanding of the LAI-SVI relationship for LAI estimation was achieved using the RTM hybrid approach, as proposed.

The best LAI - SVI relationship found with the DART dataset was the NDVI used at the genotype-scale. It was the same result for the empirical regression calibrated in the experimental dataset, which confirms the physical basis of this conclusion. Normally, a better

performance of specie-specific SVI's could be expected, such as for EucVI and GESAVI calibrated for Eucalyptus. Here, the better performance of the NDVI could be explained by its more generalist behavior. Liang et al. (2015) and Nigam et al. (2014) also found better results using this less sensitive SVI to estimate LAI of crop stands. In fact, we used the same EucVI and GESAVI equations in all simulated database and it could resulting lack of adaptability of these indices to the variety of other structural and biochemical variables of the canopy. The EucVI, which was calibrated for the same eucalyptus species in le Maire (2012), also achieved good results and could be applied to eucalyptus plantations, similar to its use in this work.

A genotype-specific calibration leads to better AIC values, which means that despite the large number of parameters to be calibrated, the advantage of having a genotype-specific relationship provides better accuracy than a global adjustment and other type of grouping. This could be explained by the fact that genotype-specific regressions integrate the combination of all the specific variables that affect SVI calibration instead of defining one specific group of variables. Colombo et al. (2003) estimated LAI by different SVI's combined with image textural information and geostatistical parameters on different vegetation types and concluded that the LAI - SVI relationship should be developed separately for each vegetation type. Darvishzadeh et al (2008) also suggested species stratification before estimating LAI by SVI's. However, grouping the genotypes in terms of leaf or litter optical properties provided intermediate results and could also be recommended. The effect of the average leaf angle that was first suspected as a relevant group was less evident, probably because only few clones had very different angles and the intra-group variability was too high.

Once the DART simulation dataset was obtained, it was a very powerful tool for further LAI estimations in eucalypts plantations; since it can be applied to any date, acquisition geometries and type of sensors, as shown in the application results. The results of the influence of the sensor type on LAI estimations and the capacity of changes between them using the DART simulation dataset enables sensor intercomparison to better understand the differences and adaptability of estimation to several remote sensing images with different spectral sensor responses. Moreover, this hybrid method allowed inferring the physical basis that affected the LAI -SVI relationship, which is an advantage of this method in relation to the direct inversion technique. Even if a direct use of regressions calibrated in DART is not possible in the current conditions, the model could be used to correct the experimental

regression of satellite images and estimate the LAI with a relatively good precision (RMSE of 0.39).

3.5 Conclusions

This study proposed a methodology to estimate the relationship between vegetation indices and LAI from DART simulations in forest plantations. We showed in both experimental and simulation dataset that:

- 1) The NDVI had the best LAI - SVI relationship using a power function (lower AIC values);
- 2) The genotype-specific group outperforms both global, stand and satellite conditions of acquisition ($AIC=0.45066 \times 10^5$, $R^2=0.97$ and $RMSE=0.29$);
- 3) A correction of the NIR band was necessary to be able to use the simulated LAI - NDVI relationship;
- 4) Once corrected, the regressions showed good estimations of independent LAI for *in situ* measurements;
- 5) The LAI estimated by NDVI changed between satellites, reinforcing the idea to have a generic simulated dataset able to calibrate different relationships in terms of sensors, acquisition characteristics, and genotypes.

References

- ATKINSON, P.M.; JEGANATHAN, C.; DASH, J.; ATZBERGER, C. Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. **Remote Sensing of Environment**, New York, v. 123, p. 400–417, Aug. 2012.
- BANSKOTA, A.; WYNNE, R.; THOMAS, V.; SERBIN, S.; KAYASTHA, N.; GASTELLU-ETCHEGORRY, J.; TOWNSEND, P. An LUT-Based Inversion of DART Model to Estimate Forest LAI from Hyperspectral Data. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, New York, p. 1–14, 2015.
- CAMPOE, O.C.; STAPE, J.L.; NOUVELLON, Y.; LACLAU, J-P.; BAUERLE, W.L.; BINKLEY, D.; LE MAIRE, G. Stem production, light absorption and light use efficiency between dominant and non-dominant trees of *e.grandis* across a productivity gradient in Brazil. **Forest Ecology and Management**, Amsterdam, v. 288, p. 14–20, 2013.
- CENTRE D'ETUDES SPATIALES DE LA BIOSPÈRE. **DART handbook**. Toulouse, 2013a. 97 p.
- _____. **DART modules user manual**. Toulouse, 2013b. 54p.

_____. **DART user manual**. Toulouse, 2014. 142 p.

COLOMBO, R.; BELLINGERI, D.; FASOLINI, D.; MARINO, C. M. Retrieval of leaf area index in different vegetation types using high resolution satellite data. **Remote Sensing of Environment**, New York, v. 86, n. 1, p. 120–131, 2003.

DARVISHZADEH, R.; SKIDMORE, A.; ATZBERGER, C.; VAN WIEREN, S. Estimation of vegetation LAI from hyperspectral reflectance data: Effects of soil type and plant architecture. **International Journal of Applied Earth Observation and Geoinformation**, Enschede, v. 10, n. 3, p. 358–373, Sept. 2008.

DA SILVA, E. V.; BOUILLET, J-P.; GONÇALVES, J. L. M.; ABREU JUNIOR, C. H.; TRIVELIN, P. OCHEUZE, C.; HINSINGER, P.; JOURDAN, C.; NOUVELLON, Y.; STAPE, J. L.; LACLAU, J-P. Functional specialization of Eucalyptus fine roots: contrasting potential uptake rates for nitrogen, potassium and calcium tracers at varying soil depths. **Functional Ecology**, Oxford, v. 25, n. 5, p. 996–1006, Oct. 2011.

GASTELLU-ETCHEGORRY, J. P.; MARTIN, E.; GASCON, F. DART: a 3D model for simulating satellite images and studying surface radiation budget. **International Journal of Remote Sensing**, Basingstoke, v. 25, n. 1, p. 73–96, jan. 2004.

GASTELLU-ETCHEGORRY, J-P., DEMAREZ, V.; PINEL, V.; ZAGOLSKI, F. Modeling radiative transfer in heterogeneous 3-D vegetation canopies. **Remote Sensing of Environment**, New York, v. 156, p. 131–156, 1996.

GASTELLU-ETCHEGORRY, J. P.; GUILLEVIC, P.; ZAGOLSKI, F.; DEMAREZ, V.; TRICHON, VDEERING, D.; LEROY, M. Modeling BRF and radiation regime of boreal and tropical forests: I . BRF. **Remote Sensing of Environment**, New York, v. 316, p. 281–316, 1999.

GILABERT, M.A.; GONZÁLEZ-PIQUERAS, J.; GARCIA-HARO, F.J.; MELIÁ, J. A generalized soil-adjusted vegetation index. **Remote Sensing of Environment**, New York, v. 82, n. 2, p. 303–310, 2002.

GUILLEVIC, P.C.; BORK-UNKELBACH, A.; GOTTSCHKE, F.M.; HULLEY, G.; GASTELLU-ETCHEGORRY, J-P.; OLESEN, F.S.; PRIVETTE, J.L. Directional viewing effects on satellite land surface temperature products over sparse vegetation canopies-a multisensor analysis. **IEEE Geoscience and Remote Sensing Letters**, New York, v. 10, n. 6, p. 1464–1468, 2013.

HERNÁNDEZ, C.; NUNES, L.; LOPES, D.; GRAÑA, M.; HOMOLOVÁ, L.; MALENOVSKÝ, Z.; CLEVERS, J.G.P.W.; GARCÍA-SANTOS, GLENDA, SCHAEPMAN, MICHAEL E. Data fusion for high spatial resolution LAI estimation. **Remote Sensing of Environment**, Amsterdam, v. 16, p. 59–67, Mar. 2014.

HUETE, A.R. A soil-adjusted vegetation index (SAVI). **Remote Sensing of Environment**, New York, v. 25, n. 3, p. 295–309, 1988.

INSTITUTO DE PESQUISAS E ESTUDOS FLORESTAIS. **Relatório anual IPEF 2012**. Piracicaba, 2012.

JACQUEMOUD, S.; VERHOEF, W.; BARET, F.; BACOUR, C.; ZARCO-TEJADA, P.J.; ASNER, G.; FRANÇOIS, C.; USTIN, S.L. PROSPECT+SAIL models: a review of use for vegetation characterization. **Remote Sensing of Environment**, New York, v. 113, p. S56–S66, Sept. 2009.

JENSEN, J.R. **Introductory digital image processing: a remote sensing perspective**. New York: Prentice Hall, 2005.

JIANG, Z.; HUETE, A.R.; DIDAN, K.; MIURA, T. Development of a two-band enhanced vegetation index without a blue band. **Remote Sensing of Environment**, New York, v. 112, n. 10, p. 3833–3845, 2008.

KUUSK, A. A fast, invertible canopy reflectance model. **Remote Sensing of Environment**, Amsterdam, v. 350, p. 342–350, May 1995.

LACLAU, J.P.; BOUILLET, J.P.; GONÇALVES, J.L.M; SILVA, E.V.; JOURDAN, C.; CUNHA, M.C.S.; MOREIRA, M.R.; SAINT-ANDRÉ, L.; MAQUÈRE, V.; NOUVELLON, Y.; RANGER, J. Mixed-species plantations of *Acacia mangium* and *Eucalyptus grandis* in Brazil. **Forest Ecology and Management**, Amsterdam, v. 255, n. 12, p. 3905–3917, June 2008.

LAURENT, V.C.E.; VERHOEF, W.; CLEVERS, J.G.P.W.; SCHAEPMAN, M.E. Inversion of a coupled canopy–atmosphere model using multi-angular top-of-atmosphere radiance data: A forest case study. **Remote Sensing of Environment**, New York, v. 115, n. 10, p. 2603–2612, out. 2011.

le MAIRE, G.; MARSDEN, C.; VERHOEF, W.; PONZONI, F.J.; LO SEEN, D.; BÉGUÉ, A.; STAPE, J.L.; NOUVELLON, Y. Leaf area index estimation with MODIS reflectance time series and model inversion during full rotations of Eucalyptus plantations. **Remote Sensing of Environment**, New York, v. 115, n. 2, p. 586–599, Feb. 2011.

le MAIRE, G.; MARSDEN, C.; NOUVELLON, Y.; STAPE, J.L.; Ponzoni, F. Calibration of a Species-Specific Spectral Vegetation Index for Leaf Area Index (LAI) Monitoring: Example with MODIS Reflectance Time-Series on Eucalyptus Plantations. **Remote Sensing**, Lower Hurt, v. 4, n. 12, p. 3766–3780, Nov. 2012.

LEBOEUF, A.; BEAUDOIN, A.; FOURNIER, R.A.; GUINDON, L.; LUTHER, J.E.; LAMBERT, M.C. A shadow fraction method for mapping biomass of northern boreal black spruce forests using QuickBird imagery. **Remote Sensing of Environment**, New York, v. 110, n. 4, p. 488–500, 2007.

LIANG, L.; DI, L.; ZHANG, L.; DENG, M.; QIN, Z.; ZHAO, S.; LIN, H. Estimation of crop LAI using hyperspectral vegetation indices and a hybrid inversion method. **Remote Sensing of Environment**, New York, v. 165, p. 123–134, Aug. 2015.

MALENOVSKÝ, Z.; HOMOLOVÁ, L.; ZURITA-MILLA, R.; LUKEŠ, P.; KAPLAN, V.; HANUŠ, J.; GASTELLU-ETCHEGORRY, J-P.; SCHAEPMAN, M.E. Retrieval of spruce leaf chlorophyll content from airborne image data using continuum removal and radiative transfer. **Remote Sensing of Environment**, New York, v. 131, p. 85–102, Apr. 2013.

NIGAM, R.; BHATTACHARYA, B.K.; VYAS, S.; OZA, M.P. Retrieval of wheat leaf area index from AWiFS multispectral data using canopy radiative transfer simulation. **International Journal of Applied Earth Observation and Geoinformation**, Enschede, v. 32, p. 173–185, 2014.

OKIN, G. S.; CLARKE, K. D.; LEWIS, M. M. Comparison of methods for estimation of absolute vegetation and soil fractional cover using MODIS normalized BRDF-adjusted reflectance data. **Remote Sensing of Environment**, New York, v. 130, p. 266–279, 2013.

RONDEAUX, G.; STEVEN, M.; BARET, F. Optimization of soil-adjusted vegetation indices. **Remote sensing of environment**, New York, v. 55, n. 2, p. 95–107, 1996.

ROUSE, J.W.; HAAS, R.H.; SCHELL, J.A.; DEERING, D.W. Monitoring vegetation systems in the Great Plains with ERTS. NASA Goddard Space Flight Center 3d ERTS-1 Symposium. **Proceedings...**United States: 1973.

SCHWARZ, G. Shwarz. **The Annals of Statistics**, Philadelphia, v. 6, n. 2, p. 461–464, 1978.

VERRELST, J.; RIVERA, J.P.; VEROUSTRAETE, F.; MUÑOZ-MARÍ, J.; CLEVERS, J.G.P.W.; CAMPS-VALLS, G., MORENO, J. Experimental Sentinel-2 LAI estimation using parametric, non-parametric and physical retrieval methods: a comparison. **ISPRS journal of photogrammetry and remote sensing**, Amsterdam, v. 108, p. 260–272, 2015.

WANG, Z.; LIU, C.; HUETE, A. From AVHRR-NDVI to MODIS-EVI: Advances in vegetation index research. **Acta ecologica sinica**, Amsterdam, v. 23, n. 5, p. 979–987, 2002.

WIDLOWSKI, J-L.; MIO, C.; DISNEY, M.; ADAMS, J.; ANDREDAKIS, I.; ATZBERGER, C.; BRENNAN, J.; BUSETTO, L.; CHELLE, M.; CECCHERINI, G.; COLOMBO, R.; CÔTÉ, J-F.; EENMÄE, A.; ESSERY, R.; GASTELLU-ETCHEGORRY, J-P.; GOBRON, N.; GRAU, E.; HAVERD, V.; HOMOLOVÁ, L.; HUANG, H.; HUNT, L.; KOBAYASHI, H.; KOETZ, B.; KUUSK, A.; KUUSK J.; LANG, M.; LEWIS, P.E.; LOVELL, J.L.; MALENOVSKÝ, Z.; MERONI, M.; MORS DORF, F.; MÖTTUS, M.; NI-MEISTERZ, W.; PINTY, B.; RAUTIAINEN, M.; SCHLERF, M.; SOMERS, B.; STUCKENS, J.; VERSTRAETAE, M.M.; YANG, W.; ZHAO, F.; ZENONE, T. The fourth phase of the radiative transfer model intercomparison (RAMI) exercise: actual canopy scenarios and conformity testing. **Remote Sensing of Environment**, New York, v. 169, p. 418–437, 2015.

4 GENERAL CONCLUSION

First, in Chapter 2 we demonstrated the good performance of DART to simulate canopy reflectance of *Eucalyptus* forest plantations. The simulated reflectance was similar to that measured by satellite very high resolution images, despite some discrepancies found in the near infrared region. Then, in Chapter 3, we showed that empirical relationships between Leaf Area Index and Spectral Vegetation Indices were able to give a reasonable precision for generic relationships, but the genotype-scale relationship provided even better results. The same methodology applied to a DART simulated dataset led to the same conclusions. An intermediate possibility of grouping the genotypes in terms of litter or leaf optical properties obtained an intermediate performance. We finally drew conclusions about the superiority of NDVI to estimate the LAI using a genotype-specific calibration. More generally, DART simulated datasets created in this work enable to calibrate different relationships regarding genotypes, sensors and acquisition characteristics.

From the results presented on this thesis and according to the topics addressed, we concluded that the Discrete Anisotropic Radiative Transfer (DART) model is a very interesting tool to simulate canopy reflectance of forest plantation and could be used:

- ✓ to estimate the leaf area index, as observed in this study;
- ✓ to estimate other biophysical parameters, such as chlorophyll. Indeed, the field campaign carried out in November 2015 also focused on measuring leaf pigments, which can be further analyzed through DART simulations.
- ✓ to understand the effect of structural variables on reflectance;
- ✓ to perform the sensitivity analysis of canopy reflectance;
- ✓ to analyze time series of data, for example, the evolution of the NDVI during the eucalypts growth in a single stand.

The three-dimensional representation of each tree crown, with the exact position of each leaf and branch, is a possibility offered by DART if this 3D object exists. The calibration of an architectural model in one of the clones under study allows obtaining a 3D representation of trees through the AMAPsim model (<http://amapstudio.cirad.fr/soft/amapsim/start>).

DART can also be used to simulate the emission of LiDAR (Light Detection And Ranging) of single or multi-pulses. The LiDAR data simulation was one of the topics that we aimed to address during this work on forest plantations; however, but it is not concluded yet.

Finally, DART also simulates light absorption, which could be compared in the future with other simpler models such as MAESTRA/MAESPA (<http://maespa.github.io/>). This model has the advantage to simulate photosynthesis of canopies.