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Towards ecologically consistent remote sensing mapping of tree communities in French Guiana

Emil Alexander Cherrington

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Towards ecologically consistent remote sensing mapping of tree communities in French Guiana: Are forest types identifiable from spatio-temporal canopy reflectance patterns?

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**TOWARDS ECOLOGICALLY CONSISTENT REMOTE SENSING
MAPPING OF TREE COMMUNITIES IN FRENCH GUIANA: ARE
FOREST TYPES IDENTIFIABLE FROM SPATIO-TEMPORAL CANOPY
REFLECTANCE PATTERNS?**

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Towards ecologically consistent remote sensing mapping of tree communities in French Guiana: Are forest types identifiable from spatio-temporal canopy reflectance patterns?

Montpellier, 15 October 2016

Emil A. Cherrington

Dedication

To the people of my native Belize, and to the people of Panamá, les États Unis, French Guiana, France, and Germany... Thank you.

The declaration "Liberté, égalité, fraternité!" of 1789 has and continues to inspire a world still thirsting for liberty, equality, fraternity, and peace...

To my wife Betzy, my late father Glenn, my mother Emelia, my grandmother Rita, Aunt Carolyn, and Aunt Katherine, for whose unconditional support I will always be indebted...

In honour of Saint Jude, the Roman Catholic patron saint of pilgrims in need and in search of deeper meanings...

And to all of our ancestors before us for the sacrifices they made and the debts they paid, and to our descendants to follow... Namaste!

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General Introduction

I. Context

Tropical forests provide important ecosystem functions (e.g. primary production, carbon and nitrogen cycling, the hydrogen cycle, etc.) as well as ecosystem services (e.g. pharmaceuticals, timber, air and water purification, climate stabilization, etc.) (Tallis et al. 2013; Virginia and Wall 2013). Despite their important role in providing such functions and services, tropical forests and the species within them are increasingly being lost, due in part to increasing deforestation (Hansen et al. 2013). One recent study, for instance, places 36%-57% of Amazon tree species at risk of extinction (ter Steege et al. 2015). Where forests are communities of trees, i.e. inter-species associations (Chave 2009; Duckworth et al. 2000; Helmer et al. 2012)) and not merely random collections of individuals, there is therefore a need to understand the patterns of the diversity of tree communities in the tropics. Understanding the patterns of tree diversity is ultimately also necessary for adequate management and conservation of tropical forests, and such information can also aid in evaluating how forests will respond to future environmental perturbations.

Tropical tree community assembly rules

Toward an understanding of the diversity of tree communities in the tropics, distinctions are made between the *processes* by which tropical tree communities form (assemble) and the spatial *patterns* formed by the assembly of such communities (Gaston and Blackburn 2000).

Processes in tropical tree community assembly

In terms of understanding the processes regarding the assembly of tropical tree communities, as one author frames the issue, “understanding the causes of spatial variation in floristic composition is one of the overarching goals of plant ecology” (Chave 2008). The two main prevailing [and competing] theories have been that of the “niche theory” and the “neutral theory” (Chave 2009).

As summarized in two studies (Madeleine et al. 2007, Chave 2009), the theory of ecological niches (Hutchinson 1957) - also termed “habitat specialization” (Chave 2008) - posits that tree species possess innate preferences for abiotic conditions and resources which will lock them into particular ecological niches via specific adaptations that make them more competitive than others in a given environment. While the issue of competition for niches has been the hallmark of the theory, later studies (e.g. Grubb 1977) have suggested “niche differentiation” as an evolutionary force counteracting the early Gause’s principle of competitive exclusion (Gause 1934). This suggests, for example, that the large number of species in the tropics is evidence of the sharing of resources both in space and in time, limiting competition between species (Schoener 1974, Madeleine et al. 2007, Péliissier 2010). Additionally, intrinsically linked to the concept of ecological niches is the concept that plants’ life history strategies will place them into certain [species-independent] “functional groups,” such as, but not limited to the following (Grime 1974; Swaine and Whitmore 1988; Oldeman and van Dijk 1991):

- Pioneers
- Light-demanding species
- Gap specialists
- Shade-tolerant species
- Non-pioneers

The “neutral theory” (Hubbell 1979; Hubbell 2001) stands in contrast to the niche theory in emphasizing that “all individuals in all species have the same prospects of reproduction and death, irrespective of the environment they grow in” (Chave 2008). Unlike the niche theory, the neutral theory is based on random (stochastic) processes and is thus not seen as deterministic, and suggests that “demographic processes may cause a rare species to be present in a community by chance rather than because it is a superior competitor” (Chave 2009). With the neutral theory, compositions of tree communities thus have more to do with stochastic processes like occasional long distance dispersal events than they do with deterministic species-habitat preferences.

Further, both competing theories have implications for observing spatial patterns of diversity of tropical forests. For instance, based on the niche theory, composition of tree communities should be more or less predictable based on the environmental factors which determine the niches. And in contrast, based on the neutral theory, composition of tree communities will depend on a range of stochastic factors such as demography, dispersal, migration, among others. Likewise, there is also evidence for the operation of both deterministic and stochastic processes in the assemblage of ecological communities. Within French Guiana in the Guiana Shield, for instance, various studies have suggested niche preferences of tropical species (Molino and Sabatier 2001, Pélissier et al. 2002, Madeleine et al. 2007). Further on the topic of French Guiana, a recent study (Guitet et al. 2015; Guitet et al. 2016) found that that beta diversity could be predicted by geomorphology, suggesting that tree community dynamics “co-evolved” over the long term along with the processes of landforms formation driven by tectonic, climatic and marine events. These results provide additional evidence for an enlarged vision of the niche theory as geomorphological landscapes may reflect imprints of past environmental filters and historical biogeographical processes that contributed to shape the actual differences in forest composition.

Those studies contrast with a limited number of other studies (Condit et al. 2002; Maaß et al. 2014) which suggest that beta diversity in the tropics are more driven by ‘neutral’ processes than by habitat specialization. In the former study, for instance, data from both Amazonia and Panama showed that the similarity between forest plots declined with distance between the plots, suggesting that the composition of the plots was heavily influenced by dispersal patterns (Condit et al. 2002). However, that same study likewise provided evidence that both dispersal and habitat specialization influenced species turnover, suggesting that aspects of both niche theory and neutral theory are at play. In terms of explaining the spatial patterns of diversity in tree communities, this suggests that one does not necessarily need to choose between niche theory and neutrality theory, as the composition of tropical forests likely reflects both niche assembly and dispersal assembly rules.

Patterns in tropical tree community assembly

While there is considerable debate among proponents of either theory (Leigh 2007, Chave 2009, Rosindell et al. 2012, May et al. 2015), such theories concern the *processes* from which the

patterns of spatial variation result (Chave 2008). Characterizing such patterns is ultimately the area into which this PhD thesis will delve, with the ambition that the detected patterns could as far as possible reflect the underlying ecological processes. That said, it bears noting that traditionally, ecological knowledge has been derived from punctual studies of the individuals comprising communities (Tucker et al. 2005, Losos and Leigh 2004, Chave 2008, Levin 2009, Péliissier 2009, ter Steege et al. 2013). Although, as pointed out in one review (Cord et al. 2013), the main advantage of field studies is that the data are highly accurate, the disadvantage is that punctual studies do not cover great spatial extents. Thus, while there are multiple networks for monitoring forest dynamics worldwide, the Center for Tropical Forest Studies (CFTS) network, for instance, only covers 11.22 km² of approximately 16.2 million km² of total forest area (FAO 2010; Anderson-Teixeira et al. 2015). That thus only covers 0.00007% of the total area of tropical forests. It is therefore unlikely, even summing the plots from other networks, that the current plot network is sufficiently representative. While that may not represent a gap in research per se, it does represent a gap in data as concerns tropical forests. Remote sensing offers opportunities to address such data gaps and gain a broader perspective on tropical forest ecology. For instance, remote sensing allows for the quantification, at global and finer scales, of changes in forest area (e.g. Hansen et al. 2013) which in turn allows for assessments of changes in the ecosystem functions and services offered by forests (e.g. Chambers et al. 2007).

Remote sensing of tropical forests

Remote sensing pertains to the acquisition of information about objects without being in direct contact with them. While remote sensing of the environment dates to the use of aerial photographs to map vegetation since the 1920s (Jensen 2006; Morgan et al. 2010), since the early 1970s, remote sensing changed with the introduction of sensors mounted on Earth observing satellites (Aplin 2004, Jensen 2006, Lillesand et al. 2007). In essence, what spaceborne sensors have allowed is for synoptic observation of entire landscapes, a feat not feasible with field measurement (Turner et al. 2003). Ideally, remote sensing permits for the upscaling of field observations. One study of the Amazon (Tuomisto 1998), for instance, explored how field measurements could be used in combination with landscape-level satellite data to understand the spatial patterns of tree diversity. Although they possess spatial scale dependencies, the spatial patterns evident in remotely sensed images – particularly imagery of the near-infrared and short-wave infrared parts of the electromagnetic spectrum – correlate with patterns of spatial variation of forests which can be measured in the field (Tuomisto 1998; Jensen 2006; Lillesand et al. 2007; Muro et al. 2016).

Remote sensing and functional traits

In terms of interpreting those spatial patterns and understanding what can be measured at large spatial scales using remote sensing, it is worth pointing out that, to date, spaceborne sensors allow for the estimation of a variety of parameters of the vegetation (Ustin and Gamon 2010), ranging from (i) forest structure (Johansen and Phinn 2006) to (ii) canopy biochemistry (Baldeck and Asner 2013) to (iii) canopy physiology (McDonald et al. 1994) to (iv) phenological variation (Viennois et al. 2013). Of the parameters proposed, Ustin and Gamon 2010 propose using static data on structure, biochemistry, and physiology (mainly to characterize *spatial* variation), while using the phenology data to assess *temporal* variation. Additionally, each of

the traits (structure, biochemistry, physiology, and phenology) also correspond to the different ways with which to observe trees or communities (depending on the scale) with remote sensing.

Organizational levels and remote sensing

On the one hand, at least since the advent of ‘very high spatial resolution’ (VHSR) remote sensing data with the launch of the commercial Ikonos satellite in 1999, a great deal of effort in remote sensing has been dedicated to the identification of individual tree species based on their canopy-level spectral response patterns (Clark et al. 2004, Lillesand et al. 2007). This essentially followed approaches pioneered much earlier (i.e. in the earlier part of the 20th Century) using [high spatial resolution] aerial photography which likewise allowed for the identification of tree species, mainly based on the textural information contained within such photographs (Morgan et al. 2010). But besides mapping individual trees, as indicated earlier, there are other ways that remote sensing can be used to examine the spatial variation of forests (tropical and otherwise).

Beyond the identification of *individual* trees, ecological remote sensing has also seen advances in terms of identifying associations of individuals, i.e. tree *communities* (Helmer et al. 2012), as well as the identification of *functional groupings* (Ustin and Gamon 2010; Huesca et al. 2015). Regarding the former concept (communities), one study (Helmer et al. 2012) showed, in the tropical forest setting of the island republic of Trinidad and Tobago, that it was possible to identify tree associations based on canopy spectral characteristics identified in both wet and dry season imagery. Nevertheless, such a concept has not been widely implemented outside of the one study, and it may just be that there are scale dependencies to identifying communities using remote sensing. That is to say following on arguments posited in Couteron et al. (2012), the spatial resolution of the input remote sensing data may limit the ability to identify tree communities if the number of individuals per unit area is high. And generally, in tropical forests, the number of individuals per unit area may indeed be high, with estimates ranging from 100 to over 200 tree species per hectare in tropical rainforests (Phillips et al. 1994, Turner 2001, Turner 2004).

Contrasting concepts of functional groups

Regarding the concept of functional groupings, a recent review paper (Ustin and Gamon 2010) suggests that it should be possible to identify plant functional types (PFTs) based on the combination of forest structure, canopy biochemistry and physiology, and phenology. Whereas it was previously mentioned that in niche theory, plant life history strategies will put individuals into broad groups like “pioneers” and “shade tolerant species” among others, the remote sensing-based plant functional type concept (Ustin and Gamon 2010) uses a concept of “functional traits”, which requires clarification as it is distinct from the classical notion of functional types in ecological theory. One comprehensive review of ecological theory on such defines functional traits as “morpho-physio-phenological traits which impact fitness indirectly via their effects on growth, reproduction and survival, the three components of individual performance” (Violle et al. 2007).

The review study (Violle et al. 2007) indicates that functional traits are particular to individuals (and must be measured at the individual level), but in considering higher organizational levels (e.g. communities and ecosystems), scaling up can be done using integration functions (Violle et al. 2007). A contrast is made between individual level “functional traits” and “community or ecosystem properties” which are “feature[s] or process[es] measured at the community or ecosystem level” (Violle et al. 2007). “Functional traits” are indicated to refer specifically to any of the following (Violle et al. 2007):

- (i) physiological processes such as photosynthesis or plant respiration,
- (ii) life history processes such as germination, growth or reproduction,
- (iii) individual fitness, or
- (iv) performance measures.

The remote sensing-based concept of functional types were termed “optical types” by their proponents (Ustin and Gamon 2010), because they are based on what optical remotely sensed imagery perceives of forest canopies. These “optical types,” however do stand in some contrast to the aforementioned ecological concept in a few ways. For one, the ecological “functional trait” concept is indicated to focus on the individual level and may differ from the “optical types,” which may apply to individuals or to higher levels of organization (i.e. communities or ecosystems), although it is hypothesized that variations in canopy reflectance even at the community scale may represent variations in functional responses at the individual level. The two concepts (the ecological concept of functional traits and the remote sensing-based one) are therefore not diametrically opposed, even as they may not necessarily apply at the same scale. This does not, however, discount the potential utility of the ‘optical type’ approach to the remote sensing of tropical forests, as, to repeat, overall variations in canopy reflectance even at even the plot level may be indicative of variations in functional responses at the individual level.

It is important to note the novelty of the “optical type” approach over other more traditional methods in remote sensing. The “optical type” approach is novel in that it combines the use of proxies for canopy biochemistry and physiology, vegetation structure and phenology - i.e. high temporal frequency data (Ustin & Gamon 2010). In contrast, traditional methods only utilize canopy reflectance estimates from imagery acquired at a single point in time or reflectance estimates averaged over time (Jensen 2006; Lillesand et al. 2007; GOF-C-GOLD 2009). In following up the “optical type” concept but utilizing only remotely sensed data on phenological variation, a recent study (Huesca et al. 2015) demonstrated the principal value of the concept in combining spatial and temporal information to address how plant communities change seasonally. That is to say, while other studies (Helmer et al. 2012) have suggested that it is possible to identify plant communities on the basis only of one time acquisition of canopy reflectance data, it is theorized that there are limitations to such approaches which can be overcome if temporal patterns as well as spatial ones are considered. In other words, and as elaborated in the following section, high frequency temporal data likely allows for observing patterns of variation of forests which obviously cannot be observed at only single points in time.

Temporal patterns

The use of temporal patterns to characterize the diversity of tropical rainforests, in fact, represents a research gap as well as a potential opportunity. Previous studies have indicated that the temporal patterns of forests observed by remote sensing pertain to seasonal phenological variation (Myneni et al. 1997, Tucker et al. 2005, Zhang et al. 2006). With regard to tropical forests, in terms of that seasonal phenological variation, it is understood that such variation is more pronounced in tropical deciduous forests than in tropical evergreen forests, i.e. tropical rainforests (Aerts 1995; Borchert et al. 2005; Bendix et al. 2006; Devi and Garkoti 2013). Nevertheless, even tropical evergreen forests such as those in French Guiana will experience seasonal phenological variation, exhibited through periodic changing of leaves (resulting in litterfall peaks), and the production of flowers (Sabatier and Puig 1985, Wagner et al. 2012). Studies of phenological variation likewise indicate that climate drives phenology, but the timing of phenological events is also linked to species-specific endogenous developmental rhythms (Kikuzawa 1995; Fenner 1998; Forrest and Miller-Rushing 2010; Méndez-Alonzo et al. 2013). In other words, phenological variation is not entirely determined by environmental variation but represents the interplay between external environmental controls and endogenous forces.

Where remote sensing allows for monitoring phenological variation, it is also important to consider what aspects of phenology can be thus observed since, as pointed out earlier, phenological variation can include flowering cycles as well as patterns of how leaves are shed or are replaced (Fenner 1998). In remote sensing, since the 1970s, computationally simple vegetation indices have been developed as ratios of the reflected light observed by satellite sensors (i.e. “spectral bands”) – mainly red and near-infrared reflected light (Tucker 1979, Lillesand et al. 2007). Field validation studies [in temperate zones] have shown that the intra-annual variation of the vegetation indices correlates principally with variation in leaf area caused by shedding (Myneni et al. 1997; Tucker et al. 2005). The correlation between seasonal variation in vegetation indices and leaf phenology has also been demonstrated in the tropics, although this has not been without some controversy (Lopes et al. 2016). The overarching message is that remote sensing data can be used to examine temporal patterns in the form of leafing phenology.

Separate from the use of [remotely sensed] temporal pattern data to monitor phenology at single sites is the concept of combining such temporal pattern data with spatial pattern data. The concept of using both spatial and temporal remote sensing data to examine forest types is not completely new, as it has been suggested in the “optical type” study (Ustin and Gamon 2010) and was implemented for Spain (Huesca et al. 2015). Still, in the context of tropical forests, only a few studies have explored such approaches. In one study of central Africa, for instance, forest types were clustered based on the temporal patterns of satellite-derived vegetation indices (Viennois et al. 2013). It was found that it was possible to develop a typology of forests in central Africa based on the combined spatio-temporal approach (Viennois et al. 2013).

Based on those previous limited applications (Viennois et al. 2013a; Huesca et al. 2015), there is therefore evidence to suggest that tropical forests in particular can be identified based on spatial and temporal patterns – at the scales of communities or ecosystems. It is theorized that a given assemblage of species will react distinctly to external environmental and endogenous drivers than a different assemblage of species. Linking that to the remote sensing, it would

then be theoretically possible to identify a given spatial pattern in terms of tropical tree species composition based on differential spatio-temporal patterns of phenological variation. It should also be emphasized that while such an approach is not completely novel since it has been implemented in temperate forests (Huesca et al. 2015), the spatio-temporal approach contrasts greatly with the current approach to characterizing (mapping) forests based only on spatial patterns of canopy reflectance obtained from single points in time, or from values averaged over periods of time. It should be expected that combining spatial patterns of canopy reflectance with how these patterns change seasonally across the year should theoretically yield a better characterization than just using data from a single date. Examining how a forest changes over time should likely yield more information on species composition than just examining a forest at a single point in time.

Limitations of remote sensing with regard to ecological applications

While it should therefore be possible to characterize the spatial variation of tropical forests (i.e. a goal in terms of understanding tropical forest diversity) using a combined spatial-temporal approach previously described, such an approach is not without obstacles to be overcome. Overcoming such obstacles will constitute a significant part of the research to be presented later in this thesis. Because [satellite] remote sensing involves observing vegetation from sensors located tens of thousands of kilometres in space, one consistent challenge has been atmospheric conditions which at times obscure the signal collected by optical satellite sensors (Jensen 2006; Lillesand et al. 2007). However, methods have been developed for correcting atmospheric effects in remotely sensed data (Vermote and Vermeulen 1999; Kotchenova and Vermote 2007; Claverie et al. 2015). In recent years, much more attention has been focused on obstacles to exploiting remotely sensed spatio-temporal data which are largely instrumental in nature (Morton et al. 2014; Soudani and François 2014; Nagol et al. 2015).

The most significant instrumental artefact described in recent years has been that of the bi-directional reflectance distribution function (BRDF), which essentially indicates that depending on the angles at which objects are viewed, they will reflect light differently (anisotropically). Such anisotropic reflectance of light is of particular interest for tropical forests because their diverse canopy architectures creates varying patterns of shading. And this also depends on the absolute elevation and azimuth of the sun, and the position of the sun relative to the viewing sensor (Roujean et al. 1992; Bicheron and Leroy 2000; Morton et al. 2014). As explored in one review study (Soudani and François 2014), forests will, in general, appear brighter (e.g. 'greener') when the sun is behind the viewing sensor and the forest is not being viewed in shade. However, if the position of the sun changes and the same forest is being viewed as it were in shade, the forest will appear less green (Soudani and François 2014). But not only will the apparent greenness of the forests change, their patterns of [satellite sensor observed] red and near-infrared reflectance will also change, because such radiation is not reflected isotropically (Soudani and François 2014). In that way, the same forest will appear different in estimated reflectance or in derived vegetation indices just on the basis of changing illumination patterns, independent of real changes in the vegetation.

There are ways of either accounting for or outright correcting for bi-directional effects (BRDF) in satellite-derived reflectance estimates. For instance, if a particular forest plot is being

observed with the same sensor view angle and under the same illumination conditions (i.e. same solar elevation and solar azimuth), it is possible to compare reflectance estimates without doing outright correction for bi-directional effects. However, imaging a forest under such conditions may be challenging for satellite sensors which generally have fixed overpass times (e.g. 10:30 am Equatorial crossing for the French SPOT-5 satellite), and the solar elevation and azimuth at a given time changes daily (Lillesand et al. 2007). But in addition to merely trying to account for BRDF, methods for outright correction of BRDF have been developed (Danaher et al. 2001; Schaaf et al. 2002; Hansen et al. 2008; Potapov et al. 2012; Flood 2013; Roy et al. 2016). Some of these correction methods generally make use of information on solar position to model reflectance based on stable solar parameters (Schaaf et al. 2002). Thus, where BRDF results in differential reflectance estimates across sensor scanning angles, BRDF corrections adjust reflectance estimates across scanning angles, effectively normalizing all views to nadir (Schaaf et al. 2002).

Returning to the topic of the use of remotely sensed spatio-temporal pattern data for monitoring seasonal changes in tropical forest, even with corrections for BRDF and methods of accounting for BRDF, there has been controversy in the application of remote sensing data. The controversy largely resolves around remotely sensed temporal data for the Amazon. In 2006 and 2007, two studies were published which made the following arguments: that tropical evergreen forests in the Amazon (i) regularly experience leaf flushing during the dry season, and (ii) experienced leaf flushing during the 2005 drought in that region (Huete et al. 2006; Saleska et al. 2007). Responses refuting the findings of both studies were forthcoming in 2010, 2012, and 2014 (Samanta et al. 2010; Samanta et al. 2012; Morton et al. 2014) and these posited instrumental and atmospheric artefacts as causing the appearance of leaf flushing.

The latter studies essentially drew into question the very feasibility of using remote sensing data to monitor tropical phenology. However, more in-depth analysis shows that the principal issue is that the earlier studies did not base their conclusions on BRDF-corrected data. Their findings were also supported by later field validation studies which have provided evidence that Amazonian forests do indeed experience dry season leaf flush (Lopes et al. 2016; Wu et al. 2016). All in all, the controversy regarding leaf flushing in the Amazon highlights the potential pitfalls to using remote sensing data for examining temporal variations of tropical forests. Likewise, they point to potential challenges applying spatio-temporal remotely sensed data for examining forest typology – as well as potential opportunities.

II. Study objectives

Taking the aforementioned review of the literature into context, the overall objective of this PhD thesis is **to evaluate the extent to which the use of remotely sensed spatio-temporal data allows for a consistent characterization of forest types via observations of canopy reflectance.**

Toward that objective, prior to examining the combined spatio-temporal patterns, it will also be useful to separately examine the spatial and temporal patterns of tropical forests because of how instrumental artefacts (caused by naturally occurring qualities like BRDF)

differentially affect patterns of spatial variation and temporal variation. To assess that, the specific research questions are as follows:

PART 1: Evaluating the spatial variation in the distribution of tropical forests

1. How do bi-directional effects affect the spatial variation of spectral response of tropical forests, and how do they affect the spatial variation of estimated distributions of forest types?
2. How do estimated spatial distributions of forest types change seasonally?

PART 2: Evaluating temporal variation of tropical forests

3. To what extent does the observed seasonal variation in vegetation indices (VIs) of tropical forests correspond to seasonal climatic variation or to instrumental or atmospheric artefacts?
4. To what extent does VI variation modelled as a function only of solar elevation change correlate with remotely sensed observations?
5. Provided that the seasonal variation in VIs is not an artefact, what do corrected data indicate in terms of the seasonal patterns for tropical forests?

PART 3: Examining combined patterns of spatio-temporal variation to identify forest types

6. To what extent can using spatio-temporal data allows for a consistent characterization of the spatial patterns of forest types?

III. Geographic scope and available data

For this study, French Guiana was chosen as the principal study area. Besides being located in the tropics (see **Figure 1**), there is ongoing research into forest dynamics in French Guiana (e.g. Molino and Sabatier 2001; Madelaine et al. 2007; Wagner et al. 2013). At higher levels of ecological organization, data on the distributions of tree communities or forest ecosystems are also lacking, although there have been multiple efforts to map French Guiana's forest types (Girou 2001; Gond et al. 2011; Guitet et al. 2015). Similarly, regarding the issue of landscape level phenology, although one study (Pennec et al. 2011) examined such patterns using vegetation indices, its findings have essentially been brought into question following a later study of the broader Amazon basin (Morton et al. 2014). Further regarding the geographic scale of the analyses performed, scales of analysis were variable (e.g. plot level versus landscape level), as is elaborated in the section on the thesis structure.

In terms of examining the thesis' research questions, there was also a great deal of data available for French Guiana. At the field plot level, available data on forest composition come from botanical transects across French Guiana and collected by researchers from different French research agencies like IRD, CIRAD, the ONF, and others. Those data are also

complemented by aerial laser scanning (ALS) data for large field sites across French Guiana, collected mainly within the last few years (~2009-2016), and mainly relevant to the issue of forest structure. Beyond the LiDAR data, the remote sensing data is also complemented by canopy reflectance estimates from a range of sensors, including Landsat-1 to Landsat-8 (1972-present), SPOT VEGETATION (1998-2014), and MODIS (2000-present).

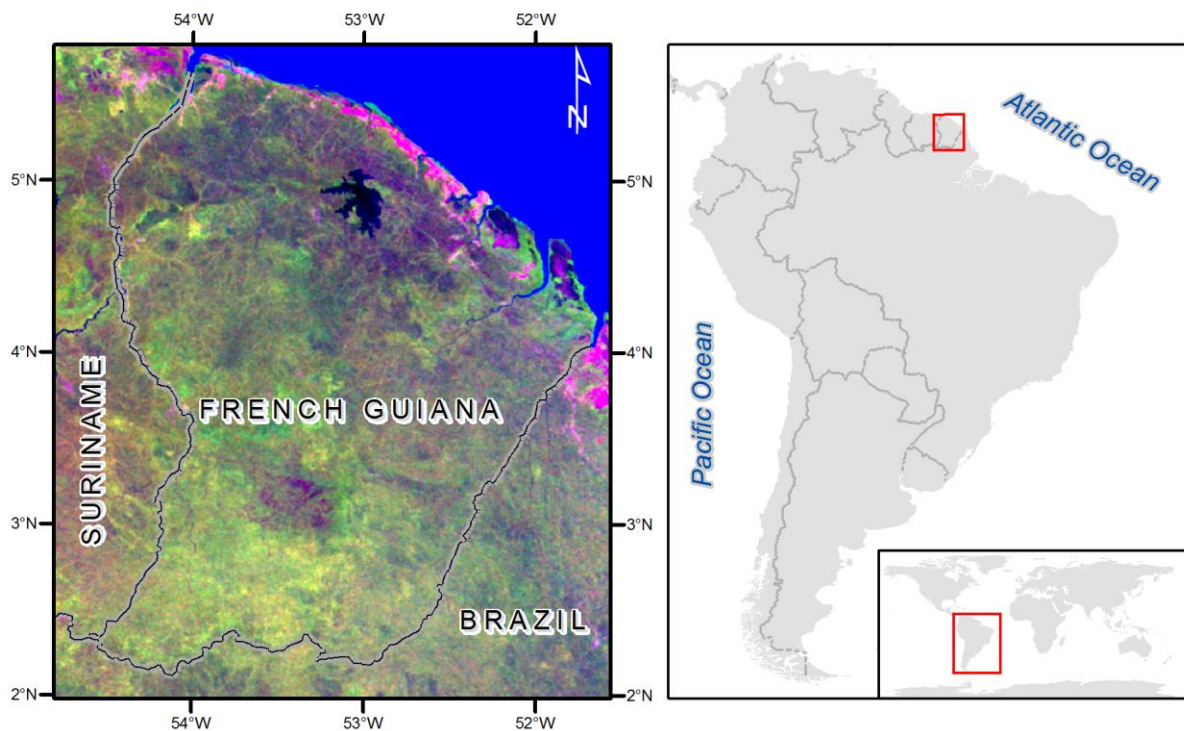


Figure 1. Left: Mean MODIS (MCD43A4)-derived reflectance imagery of French Guiana for the month of September; right: location of French Guiana in South America.

IV. PhD thesis structure

This PhD thesis takes the form of a monograph. Each of the six research questions is within the appropriate chapter. The overall conceptual flow of the thesis is presented in **Figure 2**.

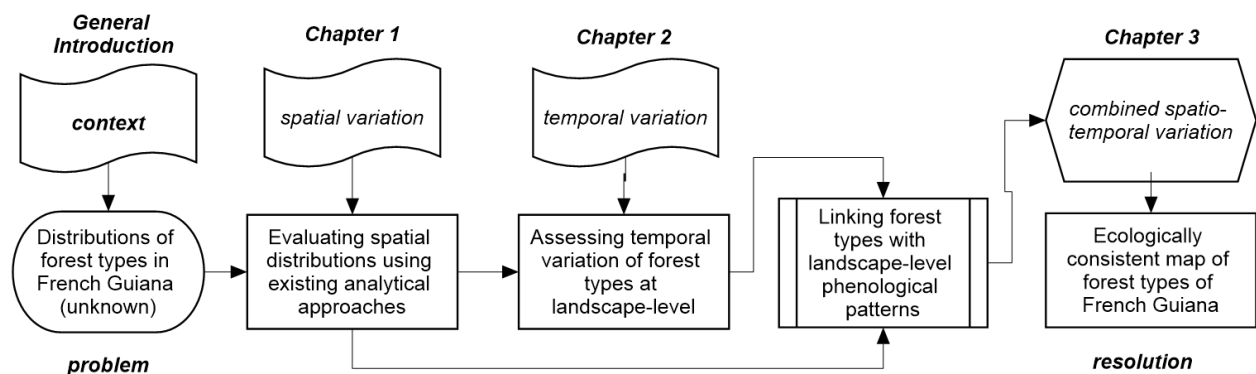


Figure 2. Links between the thesis' main chapters.

The **Methods** presents the detailed, specific methods utilized in the generating the results presented in Chapters 1-3, which themselves present the main findings of this thesis.

Chapter 1 focuses on analysis of satellite data to examine landscape-level spatial variation of French Guiana's forests. The last section of the chapter in particular examines how forests' spatial variation varies temporally and thus provides for a transition to the following chapter on temporal variation.

Chapter 2 focuses exclusively on temporal variation in French Guiana, with comparisons to forests in central Africa and northern Borneo (forests on similar geographic latitudes). The chapter addresses temporal variation at spatial scales ranging from 1 hectare plots to the territorial level (all of French Guiana) to larger landscapes spanning 10-degree by 10-degree areas across South America, Africa, and Southeast Asia. Data analysis was comprised of the use of statistical techniques for analysing time series, and radiative transfer modelling. The last section of the chapter examines the nexus between temporal variation and forest types and provides a lead-in for the following chapter which examines combined spatio-temporal variation, and a specific chapter discussion likewise the three papers' findings in context.

Chapter 3 focuses on how remotely sensed spatio-temporal patterns of variation can be used to characterize French Guiana's forests. It builds on the findings of the previous chapters and uses time-series analysis techniques to analyse spatial and temporal patterns of canopy variation to develop a forest typology for French Guiana as a proof of concept. The chapter demonstrates that it is indeed possible to map forests based on spatial and temporal patterns, in contrast with more traditional remote sensing methods.

The General Discussion synthesizes the findings of the three preceding chapters. Besides summarizing how the thesis' component studies have, overall, responded to the research questions set out in the General Introduction chapter, the General Discussion also examines the overall ecological implications of the findings. It also provides perspectives on future research directions.

Methods

I. Overview

Different methods were required to address this thesis' six research questions. For the assessment of the patterns of spatial variation of French Guiana's forests, analyses involved classifications of Landsat and MODIS data as means of characterizing spatial variation of forests. That characterization was also aided by analysis of how bi-directional effects affect canopy reflectance estimates. Complementary to those analyses, time-series data from MODIS and SPOT VEGETATION were analysed with statistical methods to characterize the seasonal temporal patterns of variation, at the landscape level. And in contrast to the characterization of spatial patterns of variation, the characterization of temporal patterns of variation were also complemented by analyses of potential environmental drivers of that variation, as well as analyses of atmospheric and instrumental artefacts' influence on such variation. The analysis of the time-series were also complemented by radiative transfer modelling simulations which allowed for understanding, at the plot level, which processes may be driving temporal variation. Lastly, where insights into spatial and temporal patterns had been gleaned, a large archive of spatial and temporal data were analysed using time-series decomposition techniques to characterize forest types.

The following sections, divided into three main axes (i. spatial variation, ii. temporal variation, and iii. spatio-temporal variation of tropical forests), present the detailed methods used to address each of this thesis' six principal research questions.

II. Evaluating the spatial patterns of variation of forest type distribution

i. Bi-directional effects and estimates of spatial variation of forest types

The following methods address the first research question, related to how bi-directional effects affect the spatial variation of spectral response of tropical forests. As elaborated in the General Introduction, the focus of the research question was to broadly understand how instrumental artefacts caused by BRDF not only affect estimates of canopy spectral response, but also the implications such artefacts have for mapping forest types in the tropics. The South American territory of French Guiana, whose approximate area is 83,534 km², was selected as the study area due to its high estimated overall forest cover (Barret at al. 2001). In terms of the coverage of the remote sensing data used to address the research question (i.e. Landsat-5, Landsat-7 and MODIS), the territory covers some eight scenes in the Landsat World Reference System-2 (see **Figure 3**), and is located entirely within MODIS tile h12v08.

Selection of a method for assessing BRDF effects in reflectance data

With regard to estimating the impacts of BRDF on the reflectance data from those sources, as a number of methods of both assessing [and correcting] the bi-directional effects in Landsat data have been proposed, part of the study design involved selection of an appropriate method for such assessment. One set of methodologies originally tested over Australia, for instance, uses the reflectance estimates from overlapping satellite overpasses to develop BRDF

correction factors based on sensor scan angles, among other factors (Danaher et al. 2001; Wu et al. 2001; Danaher 2002; Flood 2013; Flood et al. 2013).

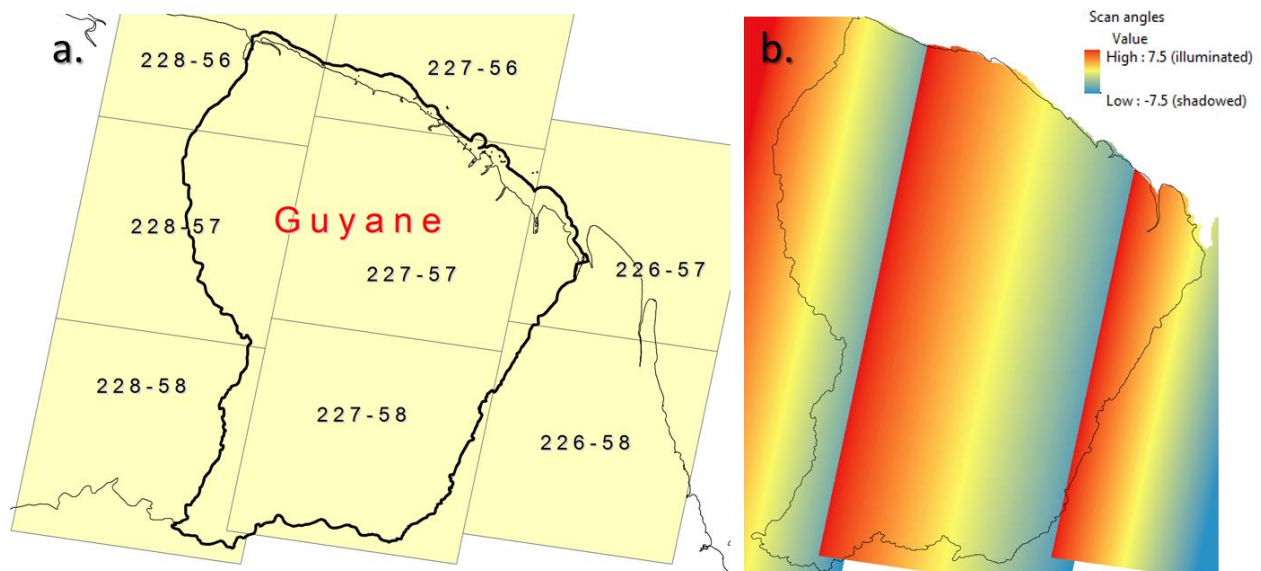


Figure 3. Landsat tiles covering French Guiana (left); Landsat sensor scan angles (right).

On the other hand, another means of assessing and correcting bi-directional effects in Landsat data is proposed by studies piloted over the Congo Basin (Hansen et al. 2008; Potapov et al. 2012). In that method, Landsat data are compared with MODIS surface reflectance estimates to determine the bias between the two reflectance estimates. However, in that approach, the authors proposed evaluating the Landsat-MODIS bias using the MOD09 surface reflectance product which is not corrected for bi-directional effects. A modification on that approach would thus be to calculate the Landsat-MODIS bias using the MODIS surface reflectance data which are already corrected for BRDF effects (i.e. the MCD43A4 product, see (Schaaf et al. 2002), and this was the approach employed in the present study. (As a caveat, it should be mentioned that it is difficult to indicate how well the BRDF correction of the MCD43A4 product is, but this was addressed somewhat by this research.) In addition to being atmospherically corrected, both the MOD09 and MCD43A4 surface reflectance are already corrected for topographic artefacts (Strahler and Muller 1999; Vermote and Vermeulen 1999).

Generation of reference MODIS reflectance dataset

Nadir BRDF-corrected reflectance estimates from MODIS from the MCD43A4 product (MODIS collection 5) were acquired from the publicly accessible NASA Reverb portal (<http://reverb.echo.nasa.gov/reverb/>) for the period July 2002 – March 2014 for the h12v08 tile which covers French Guiana. The quality assessment / quality control (QA/QC) flags from the corresponding MCD43A2 product were used to filter the reflectance data by extracting only data corresponding to “best quality, full [BRDF] inversion” (Schaaf et al. 2002). Since the Landsat data to which the MODIS reflectance was to be compared corresponded to data from September (of different years), a single September composite of the filtered MCD43A4 data was generated by averaging reflectance data corresponding to the multiple, overlapping 16-day datasets which cover September. These included the data for Julian days 241 (29 August

to 13 September), 249 (covering 6-21 September), and 257 (14-29 September). Averaging the data over the period indicated was used as a means of both reducing noise in the MODIS reflectance data, and maximizing the number of observations over French Guiana, necessitated by shifting cloud cover. Further, the September composite was assembled by using minimum reflectance in all of the spectral bands, with the exception of the near-infrared band, for which maximum reflectance was extracted. This was also done as a means of removing noise, as proposed in an earlier study (Hansen et al. 2003). As evidenced by earlier research, aerosols tend to increase spectral reflectance in most visible and mid-infrared parts of the electromagnetic spectrum, but they actually decrease spectral reflectance in the near-infrared part of the spectrum (Kaufman et al. 1992). Hence, compositing using the maximum near-infrared reflectance will tend to remove aerosol-contaminated pixels.

Generation of Landsat surface reflectance dataset

The assembly of a Landsat surface reflectance mosaic for French Guiana involved more data processing than that of assembling the MODIS mosaic (see **Figure 3**). For one, imagery from multiple dates with slightly differing illumination conditions had to be selected because of persistent cloud cover over French Guiana, which is even a problem in the dry season. The imagery used were acquired via the U.S. Geological Survey’s Glovis portal (<http://glovis.usgs.gov>), and had acquisition dates ranging from 27 September 2005 to 5 September 2009 (**Table 1**). Where reflectance is known to be impacted by solar elevation, it should be noted that the images had a maximum difference in solar elevation of only 2 degrees (Nagol et al. 2015).

Table 1. Landsat imagery used for the creation of an image mosaic of French Guiana.

No.	Landsat Path-Row	Location	Satellite / Sensor	Date	Solar elevation	Solar azimuth
1	226-57	northeast	Landsat-7 ETM+	28 Sept. 2008	62.3°	103.5°
2	226-58	southeast	Landsat-7 ETM+	28 Sept. 2008	62.4°	100.7°
3	227-56	north central	Landsat-7 ETM+	27 Sept. 2005	62.3°	105.2°
4	227-57	central	Landsat-7 ETM+	27 Sept. 2005	62.5°	102.4°
5	227-58	south central	Landsat-7 ETM+	27 Sept. 2005	62.5°	99.6°
6	228-56	northwest	Landsat-5 TM	2 Sept. 2008	60.5°	84.7°
7	228-57	central west	Landsat-5 TM	5 Sept. 2009	61.5°	84.1°
8	228-58	southwest	Landsat-5 TM	5 Sept. 2009	61.1°	81.5°

Following acquisition of the images, three image strips were generated using the mosaic function in the ArcGIS software platform, corresponding to eastern, central, and western French Guiana. Due to the absence of data from every 7th line of Landsat-7 data caused by the Scan-Line Corrector malfunction, the Landsat-7 image strips were further processed using the “Frame and Fill” software package to fill the data gaps using the most cloud-free data from other dates (Lillesand et al. 2007, Irish 2009). Following gap-filling, the image strips were atmospherically corrected to remove the effects of haze using the haze optimization transform method included in the ATCOR package (Zhang et al. 2002; Richter and Schlaper 2016).

In contrast with other available tools, ATCOR was selected for the image atmospheric corrections because that correction was also coupled with topographic correction, which was necessary due to the complex topography of French Guiana (Richter & Schlaper 2016). The topographic correction – which made use of the 30m SRTM digital elevation model of French Guiana – aided in minimizing the distortions that topographic shadowing has on surface reflectance (Richter and Schlaper 2016). Via such processing, the Landsat data were transformed from digital numbers to estimates of surface reflectance, comparable to the surface reflectance estimates of MODIS, albeit at different spatial resolutions (i.e. 30m vs. 463m). As a final step, the data were also masked of clouds and cloud shadows using masks generated via use of the CLASlite software package (Asner 2009; Asner et al. 2010). Complementary to this, for the Landsat data, raster surfaces of the approximate sensor scan angles were generated (Figure 3). For the forest type mapping, the Landsat surface reflectance data were also adjusted for BRDF using the September reference reflectance dataset which had been assembled from the MODIS MCD43A4 Nadir BRDF-adjusted Reflectance (NBAR) data (Schaaf et al. 2002). This was done by generating, band by band, BRDF adjustment factors from the Landsat-MODIS reflectance differences. This adjustment resulted in the development of a wall-to-wall, BRDF-corrected Landsat mosaic of French Guiana.

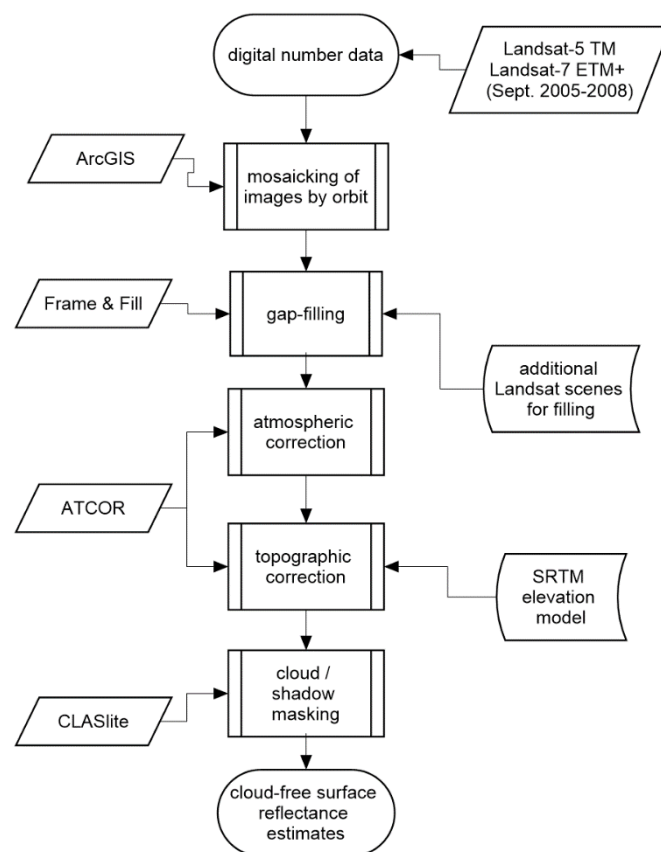


Figure 4. Work flow of Landsat data processing for BRDF assessment.

Evaluation of anisotropy in reflectance data

The subsequent step in the assessment consisted of examining the degree of anisotropy in the reflectance data, across the sensors' scanning angles. This consisted of examining how the

Landsat surface reflectance estimates varied with the scanning angle, looking for residual anisotropy in the BRDF-corrected MODIS reflectance estimates, and examining the degree to which the differences between surface reflectance from MODIS and Landsat were dependent on the scan angle. In order to compare the Landsat and MODIS surface reflectance estimates, the Landsat data were resampled up to the resolution of the MODIS data (i.e. 463m), using the resample function in ArcGIS (McCoy et al. 2001). Nearest neighbour resampling was chosen as it mostly preserved the original spectral values, relative to other resampling methods which may have distorted the reflectance values (Jensen 2006; Lillesand et al. 2007; Studley and Weber 2011).

Following this, spectral band by spectral band, the data from the two sources were compared, using the raster subtraction function of ArcGIS (McCoy et al. 2001), allowing for pixel-to-pixel comparisons, to indicate the extent to which the reflectance estimates differed. The results of those comparisons were raster surfaces whose individual pixels indicated the differences in reflectance between MODIS and Landsat. Absolute reflectance differences exceeding 5% were considered to be caused by factors other than BRDF, and were filtered out, as these might reflect differences due to land clearings between the two image dates or residual clouds or cloud shadows, with the 5% threshold following an earlier study (Potapov et al. 2012). Where those differences varied spatially, mean estimates of the differences per band were reported as a means of understanding how BRDF impacts each spectral band globally, and not locally.

Complementary to the calculations of the reflectance data differences, simple statistical analyses were also done using the raster data and linear models constructed in the software platform R (R Foundation 2011) to assess the following (with β_j as the model coefficients and ε_i the model error):

- i. the extent to which the Landsat reflectance estimates varied across the scanning track (Landsat reflectance_{*i*} = $\beta_0 + \beta_1$ scan angle_{*i*} + ε_i)
- ii. the extent to which the MODIS reflectance estimates varied across the scanning track (MODIS reflectance_{*i*} = $\beta_0 + \beta_1$ scan angle_{*i*} + ε_i)
- iii. the extent to which differences in reflectance between MODIS and Landsat were correlated with the Landsat sensors' scan angles (Reflectance difference_{*i*} = $\beta_0 + \beta_1$ scan angle_{*i*} + ε_i)

In the case of the above, it is assumed that the anisotropy of the Landsat reflectance follows a linear function with respect to the view zenith angle. By contrast, if MODIS imagery are properly corrected for BRDF, such linear effects should not be noted in MODIS reflectance data. Following the assessment of anisotropy, the spatial distribution of forest types were evaluated, with the overall approach used in that forest type mapping depicted in **Figure 5**. Further, to test the impact of BRDF on the mapping of French Guiana's forest type, a dual-pronged approach was tested:

- i. using imagery not corrected for BRDF effects, and
- ii. using imagery corrected for BRDF effects.

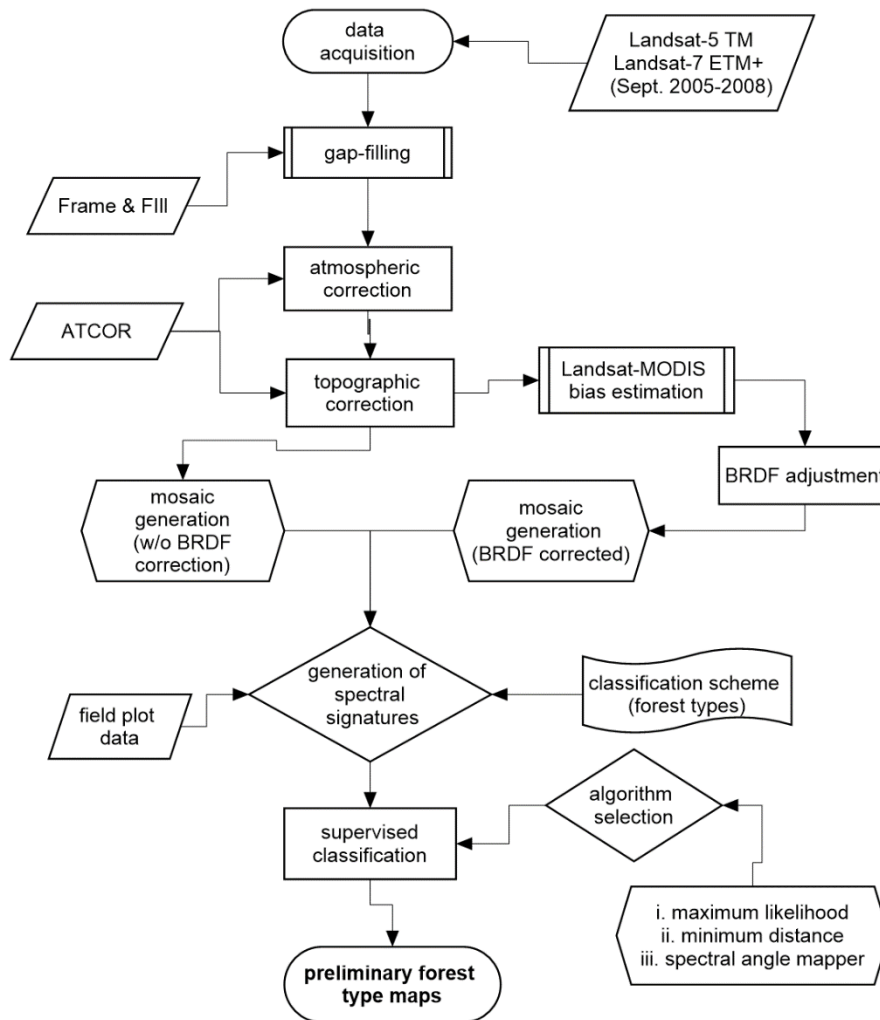


Figure 5. Workflow for mapping of French Guiana’s forest types using Landsat data.

Forest type mapping

While there are multiple ways of mapping forests using remote sensing, the present analysis focused on use of the ‘classical’ supervised spectral classification approach, arguably the most common approach used for forest type mapping (Lillesand et al. 2007). As one of the main inputs to supervised classification is a classification scheme, as a first filter, a preliminary forest classification scheme was developed based on data from botanical transects, including the types of forests listed in **Table 2**.

Per the workflow, in order to evaluate the impacts of bi-directional effects on the reflectance data, as indicated previously, two separate data streams were used in the classification, i.e. (i) data not corrected for BRDF, and (ii) data corrected for BRDF. For the classification itself, field plot data was utilized along with the imagery to generate spectral signatures of the respective forest types. Supervised classification was then performed on the two mosaics, using the maximum likelihood classification algorithm, generating preliminary forest type maps. Via the maximum likelihood classification approach, individual pixels from the Landsat mosaics were mapped to one class (of the 15 classes indicated in **Table 2**) to which they were most similar spectrally (Lillesand et al. 2007). In that sense, a classification is merely a clustering

approach, where pixels are assigned to a class (i.e. “classified”) depending on spectral characteristics. A classical pixel-based classification approach was selected over object-oriented classification because the research indicated that the latter was more suited to use with very high spatial resolution imagery, which is not the case of the Landsat data used (Lillesand et al. 2007, GOFC-GOLD 2012).

Table 2. Classification system used in mapping French Guiana’s forest types.

No.	Class	Forest type (where applicable)
1		Forests with regular canopies
2		Forests with dissected canopies
3		Forests with open canopies
4		Low, dense forests
5		Secondary and degraded forests
6	Forest	Cloud forests
7		Forests on sandy soils
8		Swamp forests
9		Mangrove-dominated forests
10		<i>Parinari campestris</i> -dominated forests
11		Bamboo-dominated forests
12		Liana-covered forests
12		Impervious surfaces or bare soils
13	Non-forest areas	Savanna
14		Wetlands
15		Inland water bodies

In addition to classifying the Landsat imagery into forest types, as a control, 463m spatial resolution MODIS imagery from MODIS Terra (MOD09 product) and MODIS Aqua (MYD09 product) were classified to compare with the Landsat-derived maps (Vermote and Vermeulen 1999). The MODIS images were selected for their low cloud cover and were collected in the morning (Terra) and afternoon (Aqua) of 27 September 2005, and thus coincided precisely with the date of the imagery of the central column of the Landsat mosaic (making differences in atmosphere and phenology negligible). Those MOD09 / MYD09 data, however, are not corrected for BRDF.

Comparison of forest type maps

Following the generation of the forest type maps via supervised classification, those maps were compared. Simple comparison was done using the ‘Raster Calculator’ tool of the ArcGIS 10.3 platform to examine where the classification results coincided and did not coincide. This allowed for assessing the degree of agreement between the maps. Further visual analysis was conducted by comparing the forest type maps with a maps of sensor scan angles which were obtained for the input Landsat and MODIS imagery (**Figure 6**). This allowed for analyzing the extent to which the spatial patterns of forest types did or did not match the sensor scan angles (a characteristic of BRDF).

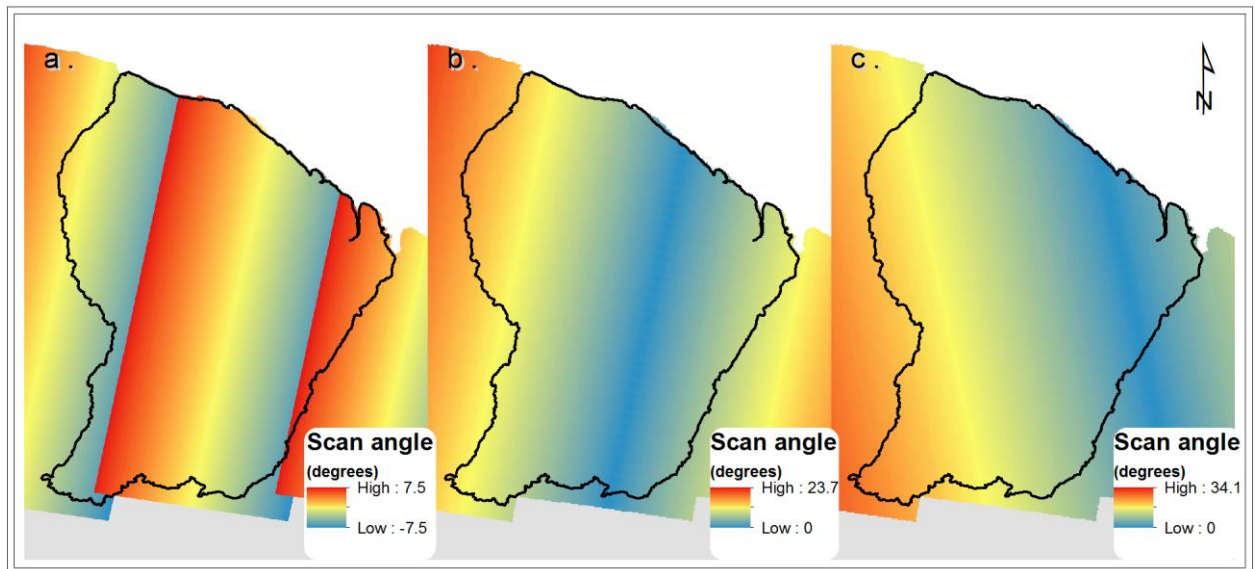


Figure 6. Sensor scan angles: a. for the Landsat images used, b. for the MODIS Terra data, and c. for the MODIS Aqua data.

Validation

While field validation of the forest type maps would have been ideal, due to time constraints, this could not be done. Nevertheless, the effectiveness of the BRDF correction was evaluated by comparing the extent to which the reflectance estimates (BRDF-corrected and uncorrected) contributed to the ability to spectrally discriminate forest types. As such, measures of spectral separability were calculated using the Jeffries-Matusita measure of spectral separability (Richards and Jia 2006), using the field plot data in concert with the BRDF-corrected and uncorrected surface reflectance estimates. The Jeffries-Matusita measure provides pair-wise comparisons of the reflectance data to determine how spectrally distinct the respective spectral signatures are, and in that sense served as a sort of proxy for validation (Richards and Jia 2006). Regarding the 12 forest types evaluated, Jeffries-Matusita estimates were provided for 66 unique pair-wise comparisons.

ii. Effects of seasonality on mapping the spatial variation of forest types

Complementary to the evaluation of how BRDF effects impact estimates of forest type distribution, additional analyses concentrated on understanding how estimates of forest type distribution vary temporally in data already corrected for BRDF. This was related to the second research question, which focused on how estimates of spatial distributions of tropical forest types change seasonally. Overall, the methods consisted of (i) extracting reflectance data for the forest cover classification, (ii) the mapping of forest types, (iii) evaluation of the separability of the forest types, and (iv) the estimation of the number of spectrally distinct forest types in each reflectance image. With regard to extracting the reflectance data, due to the low rate of land use change in French Guiana, estimates of mean monthly reflectance were derived, as the territory's forests can be considered 'stable.' That reflectance data was compiled using the 463m resolution nadir BRDF-adjusted MCD43A4 reflectance data, which was used in place of the more commonly used MOD09 surface reflectance data. Data were acquired for the h12v08 tile in MODIS' reference system, which includes all of French Guiana

and Suriname, most of Guyana, and a part of Brazil's Amapá state. The MCD43A4 data are available for 46 overlapping 16 day periods, which over the 15 year time period studied amounted to 688 datasets spanning Feb. 2000 - Feb. 2015. Data were extracted for 6 of MODIS' 7 spectral bands (excluding the 1230-1250nm spectral band). Quality assessment flags from the complementary MCD43A2 data were used to extract only the highest quality reflectance data.

For each 16 day period, an 'average' was computed as follows: for all of the spectral bands with the exception of the near-infrared band (MODIS band 2), the 15-year minima were calculated, and for the NIR band, the maxima were calculated. This mirrored the approaches used in previous studies (Hansen et al. 2003; Viennois et al. 2013) and allowed for filtering noise from the respective spectral bands. Data were then grouped according to the approximate calendar months they pertain to, and those reflectances were averaged to generate mean monthly reflectance estimates (based on the 15-year time-series). As the MODIS h12v08 tile covers much of the Guiana Shield, data were spatially subset to the extent of French Guiana. However, as shown in **Figure 7** (derived from the resulting data), even using the 15 years of acquisitions, missing data due to cloud cover was still an issue, particularly during the first half of the year (the rainy season). Although only August and September had 100% coverage, July to December was generally cloud-free. Thus, for this analysis, only the data from July-December were used to evaluate forest type discrimination. A 3x3 low-pass filter was applied to the reflectance data to smooth the data and by so doing remove the 'salt-and-pepper' pattern observed (Lillesand et al. 2007).

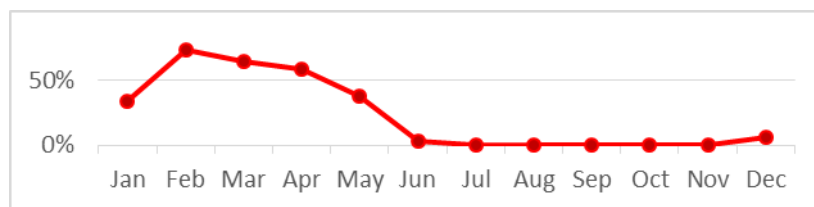


Figure 7. Percent missing data for French Guiana in the monthly mean archive of MODIS MCD43A4 reflectance data for the period July 2002 – March 2014.

To attempt to drill deeper into the forest types of French Guiana, a preliminary classification system was devised, based on a combination of field plot data from both CIRAD and IRD, and types of forest which appeared visibly distinct in the false colour combinations of the satellite imagery. For the forest cover classification, training data regions of interest (ROIs) were digitized directly from the imagery, in the ENVI platform. Originally, some 20 land cover classes were selected, of which 15 were seen as distinct forest types (and 5 non-forest classes). Using ENVI's n-D visualizer function, the training data were refined, and the 20 classes were condensed into 15 classes: 13 forest classes and 2 non-forest classes (**Table 2**). Forest types were then mapped using the ROIs and the reflectance data, respectively for August and the annual data, via the Maximum Likelihood supervised classification algorithm.

Where the main focus of this study was to assess the discrimination of forest types, simple statistical analyses were run using ENVI's ROI separability function, which generates the Jeffries-Matusita measure of spectral distance. The entire range of possible class pairs is compared and analysed for statistical 'distance,' with possible distance values ranging from

0-2, and with the Jeffries-Matusita measure of distance, pairs with distance values at or exceeding 1.9 are indicated to have a high degree of separability (Richards and Jia 2006). Distance measures were thus calculated for the reflectance data for July-December, at 463m resolution, with the following spectral band combinations: (i) all 6 spectral bands, (ii) the visible and near-infrared bands, VNIR (blue, green, red, near-infrared – MODIS bands 1234), (iii) the red, near-infrared, and 2 shortwave infrared (SWIR) bands – MODIS bands 1267, and (iv) the 3 bands used in an earlier study (Gond et al. 2011) study – red, near infrared, and shortwave infrared (MODIS bands 126). Complementary to the analysis of spectral separability, a parallel effort to estimate the number of spectrally distinct forest types was conducted by using the ISODATA unsupervised classification algorithm on the 6 monthly reflectance datasets. Prior to ISODATA clustering, non-forest cover was masked from the data. For each monthly reflectance dataset, mean Enhanced Vegetation Index (EVI) was also derived using the standard equation (Huete and Justice 1999), and an index of noise in the reflectance data was generated by deriving the mean slope of each spectral band and averaging by the number of bands.

III. Evaluating the temporal patterns of variation of tropical forests

Complementary to the evaluations related to the spatial patterns of variation of tropical forest (the first axis of this research) were analyses related to the temporal patterns of variation of tropical forest (the second axis of this research).

i. Assessing seasonal variation of vegetation indices at the regional level

The first part of the assessment of temporal patterns of variation addressed this thesis' third research question, which was related to the extent to which observed seasonal variation in vegetation indices (VIs) correspond to seasonal climatic variation or to instrumental or atmospheric artefacts. This particular set of analyses also focused on VI variation at the regional level. With a wide variety of satellite-derived VIs available for such analysis, this study focused on analysis of data from 3 indices: (i) the Enhanced Vegetation Index, EVI (derived from MODIS' MCD43B4 product), (ii) the fraction of green vegetation cover index, FCOVER (derived from VGT), and the Leaf Area Index, LAI (derived from VGT).

EVI, on the one hand, estimates “the ‘green’ vegetation signal across a global range of vegetation conditions while minimizing canopy influences associated with intimate mixing by non-vegetation related signals” (Huete and Justice 1999). FCOVER, in turn, estimates “the fraction of green vegetation covering a unit area of horizontal soil... correspond[ing] to the gap fraction in the nadir direction,” and is said to be “a very good candidate for substitution of classical vegetation indices” (Camacho et al. 2009). LAI corresponds to “half the total developed area of green elements per unit horizontal ground area” (Baret et al. 2013). EVI is derived from ratios of blue, red, and near-infrared reflectance, while FCOVER and LAI are both generated by radiative transfer model inversion and application of neural network algorithms to red, near-infrared and shortwave infrared reflectance data of VGT (Baret et al. 2013; Huete and Justice 1999). EVI and FCOVER were generated from nadir-normalized imagery, precluding potential view angle effects (Schaaf et al. 2011; Camacho et al. 2009).

Data were acquired from NASA's Reverb system and the European Commission's Copernicus Global Land Service (both publicly accessible). Data were acquired for the 139-month period spanning September 2002-March 2014, chosen mostly for the temporal overlap between SPOT VEGETATION and MODIS (Aqua and Terra). The study area consisted of three 10 degree x 10 degree zones located on the equator (**Figure 8**), and corresponding to tiles h12v08, h19v08, and h29v08 in MODIS' reference system. The westernmost tile (1) covers most of the Guianas (i.e. the Guiana Shield), including all of French Guiana and Suriname, most of Guyana and the Brazil's state of Amapá. The central tile (2) covers an area of central Africa including the majority of Cameroon and Equatorial Guinea, half of the Central African Republic, and parts of Nigeria, Gabon and Congo. The easternmost tile (3) covers the northern half of the island of Borneo, including all of Brunei, and parts of Malaysia and Indonesia. As the areas were extensive and covered a range of ecosystems, for standardization, only evergreen forests were considered, using a mask derived from the European Space Agency's 2009 GlobCover map.

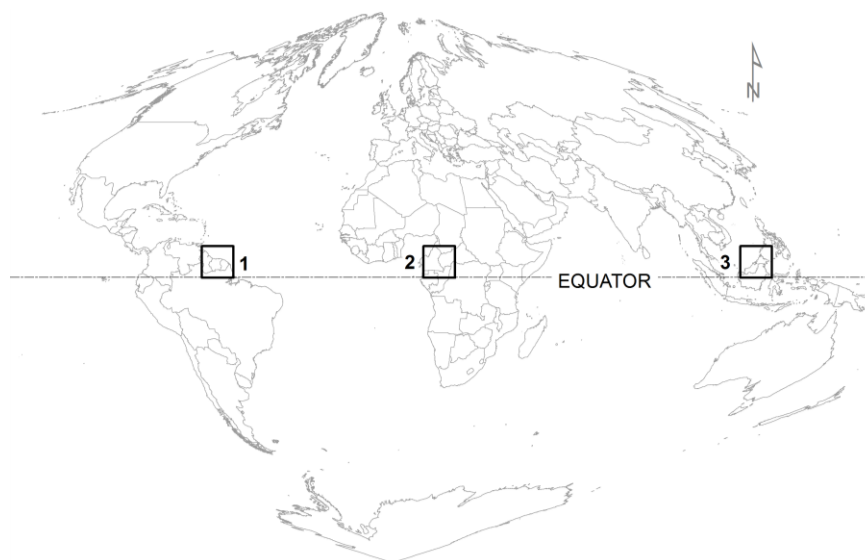


Figure 8. Location of the study areas for regional-level assessment of VI variation (1: Guiana Shield, 2: central Africa, 3: northern Borneo).

The mask also allowed for eliminating possible impacts from tropical deciduous forest, which display strong phenological variation. Also, due to potential issues of land use change in these regions which might also impact the VI estimates, only the largest contiguous blocks of forest were analysed, restricting the area of tropical evergreen forest sampled in each zone. In the Guianas, the extent of forest analysed was 89,368 km² (13.5% of that zone's forest area), while for the central Africa zone, the area was 100,804 km² (15.3% of that zone's forest area), and for Borneo, it was 12,811 km² (3.5% of that zone's forest area). Those zones were used for extracting mean monthly values for EVI, FCOVER, and LAI over the 139-month period.

Table 3. Factors used in regression and correlation analyses.

No.	Variable	Source
1	Solar elevation (SElev)	NOAA ephemeris
2	Aerosol optical depth (AOD)	MODIS Terra MOD08 M3 v6
3	Cloud fraction (CF)	AIRS AIRX3STM v6
4	Incident shortwave solar radiation (SW)	GLDAS NOAH model L4, version 1
5	Incident longwave solar radiation (LW)	GLDAS NOAH model L4, version 1
6	Surface temperature (TMP)	AIRS AIRX3STD v6
7	Precipitation (PCP)	TRMM 3B43 v7
8	Soil moisture, 0-200cm (SM)	GLDAS NOAH model L4, version 1

To analyse the annual variation in VIs, eight explanatory variables were selected based on the hypotheses underlying this study (see **Table 3**). That is to say, the variables were selected as proxies for three main factors: (i) BRDF (e.g. solar elevation as a driver of BRDF), (ii) atmospheric factors which contaminate spectral reflectance data (cloud cover and aerosols), and (iii) environmental / climatic drivers (precipitation, radiation, rainfall, and soil moisture). Mean monthly values over the 12 years (not normalized) were extracted, based on the zones mentioned. Except for solar elevation, all data were acquired from NASA's Giovanni online data system, and corresponding to the same period as the VI data. Based on the hypotheses, the following linear regression models were developed, in which the subscript i indicates the mean monthly values of VIs and explanatory variables over 2002-2014, the β are the model coefficients and ε the model error:

- **Model 1 (BRDF):** VI as a function of solar elevation ($VI_i = \beta_0 + \beta_1 SElev_i + \varepsilon_i$)
- **Model 2 (ATM):** VI as a function of atmospheric factors ($VI_i = \beta_0 + \beta_1 AOD_i + \beta_2 CF_i + \varepsilon_i$)
- **Model 3 (ENV):** VI as a function of environmental factors ($VI_i = \beta_0 + \beta_1 PCP_i + \beta_2 TMP_i + \beta_3 SM_i + \beta_4 SW_i + \beta_5 LW_i + \varepsilon_i$)

Sub-models were also developed, as well as complete models exploring the variation explained by the combined effects of BRDF, atmospheric, and environmental factors. Model fit was assessed via the coefficient of determination (R^2) and the Akaike Information Criterion (AIC), and the residual standard error (RSE) of each linear regression was also computed (Crawley 2013). Pair-wise correlations were used to compare VIs between regions, and to compare the explanatory variables (using the Pearson product-moment correlation coefficient, Pearson's r). The Kruskal-Wallis multiple comparison test was used to look for statistically significant differences among monthly VI values.

ii. Assessing seasonal variation of vegetation indices at the plot level

Related to the previous evaluation, it was likewise decided to examine the issue of VI variation, but at the plot level, to complement the regional level analyses. That analysis addressed the fourth research question regarding the extent to which VI variation modelled as a function only of solar elevation change correlates with actual remotely sensed observations. As case studies for other tropical regions, three 1-ha plots within French Guiana representing distinct forest structures and topography were selected as study sites (**Figure 9**). As indicated in **Table 4**, the northernmost plot, at Paracou, possesses the forest with the

greatest mean canopy height, a moderate terrain slope, a high vegetation density as indicated by a high mean Plant Area Index, and the highest degree of canopy closure of the three sites. In contrast, the plot at Nouragues was the site with the largest gap fraction, but with a mean canopy height of over 24m, a similar PAI to the plot at Paracou, and it lies on largely flat terrain. The plot at Itoupé is on an eastern-facing slope of a mountain almost 800m above sea level, and possessed the highest terrain slope of the three plots. Its forest also possessed the lowest vegetation density of the three plots, and its estimated mean canopy height was not as high as the other two plots. Overall, the three sites all possess rough canopies, albeit with a gradation from Paracou to Nouragues and Itoupé as indicated by two particular metrics, the high mean canopy height slope, and the standard deviation of the canopy surface elevation (see **Table 4**).

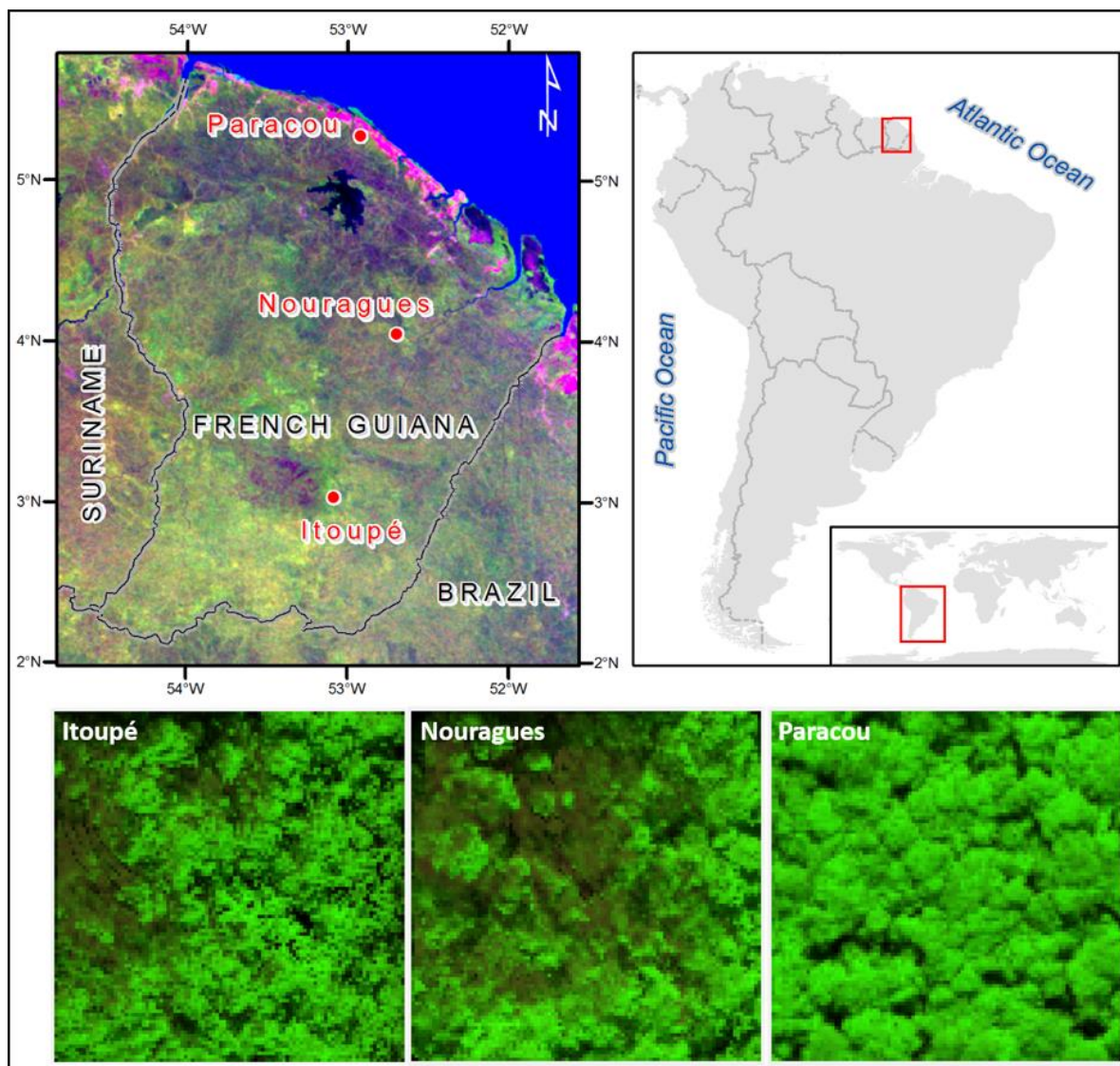


Figure 9. Top: Location of the three 1-ha plots across French Guiana, overlain on mean MODIS (MCD43A4)-derived reflectance imagery for September; bottom: simulated false colour imagery (MODIS band combination 1-2-3) of plot canopies generated from aerial-LiDAR data and radiative transfer modelling.

Table 4. Study site characteristics, with mean stand parameter of 1-ha plots as extracted from the aerial LiDAR data.

Site	Mean elevation above sea level	Mean terrain slope	Mean canopy height	Mean canopy height slope	Std. dev. of canopy surface elevation	Mean plant area index	Canopy gap fraction
Itoupé	781.5 m	26.0°	21.8 m	63.3°	16.8	10.8	5.84%
Nouragues	156.6 m	2.4°	24.3 m	60.4°	9.1	13.2	7.6%
Paracou	21.4 m	8.0°	29.3 m	43.1°	4.8	13.3	0.8%

Remote sensing data

High density multi-return aerial LiDAR (aerial laser scanning, ALS) data have been acquired in August 2014, October 2015 and September 2013 for Itoupé, Nouragues and Paracou sites, respectively (full metadata available at: <http://vmcebagn-dev.ird.fr/geonetwork/srv/eng/search>). These data were used for extraction using LAStools software suite (Hug et al. 2012), of plot digital elevation models (DEMs) from LiDAR ground returns, digital surface models (DSMs) from top of canopy LiDAR returns and canopy height models (CHMs) from the difference between DSMs and DEMs. These models, computed at 2m spatial resolution were then used to derive stand structure parameters as given in **Table 4**. Canopy roughness was characterized by: (i) mean canopy height slope, which corresponds to the average value of the slope of the top of the forest canopy, with low value of mean canopy height slope indicating that there was not much canopy ‘topography’; (ii) the standard deviation of the DSM. The canopy gap fraction as estimated from the CHM by calculating the proportion of cells below 10m. The Plant Area Index in turn was extracted from the LiDAR point cloud using AMAPvox platform [15] that was also used to generate 3D stand mock-ups for radiative transfer modelling.

Toward the radiative transfer modelling, data on solar position were acquired from an online solar position calculator from the U.S. National Oceanographic & Atmospheric Administration, NOAA (<http://www.esrl.noaa.gov/gmd/grad/solcalc/>). Solar elevation and solar azimuth data were acquired for the 15th of each month, with the exception of February (for which data for the 14th was acquired). Data were also acquired on an hourly basis for 15 September and 15 December, corresponding respectively to dry and wet season months, as well as the respective months with the highest and lowest mean solar elevations.

For the sake of comparison with radiative transfer models outputs derived from ALS data acquired from field plots overflights, MODIS satellite data for 2004-2013 was also acquired: 463m resolution BRDF-corrected MODIS surface reflectance data (MCD43A4 product); 1 km resolution Leaf Area Index (LAI) data from MODIS (MCD15A2 product); ~25 km Aerosol Optical Depth (AOD) from MODIS (MOD08 M3 v6 product). The MCD43A4 and MCD15A2 data were acquired from the NASA Reverb portal (<http://reverb.echo.nasa.gov/reverb/>), while the AOD data were acquired from NASA’s Giovanni platform (<http://giovanni.gsfc.nasa.gov/giovanni/>). Enhanced Vegetation Index (EVI) estimates were derived from the MODIS reflectance data using the standard algorithm, and the data were

extracted for the pixels corresponding to the Paracou plot, to facilitate comparison with the radiative transfer modelling outputs (Huete and Justice 1999).

ALS-derived 3D stand mock-ups and radiative transfer modelling

To generate inputs for the radiative transfer modelling, the LiDAR point clouds and accompanying DEMs were processed with the AMAPvox platform (<https://amap-dev.cirad.fr/projects/voxelidar/wiki>), which produces a 3D voxelized representation of a forest scene from ALS data (Vincent et al. 2015). LiDAR signal attenuation through the canopy is analysed using a ray-tracing algorithm to yield a local transmittance estimate. For each voxel (2 m x 2 m x 2 m in the present study), local transmittance was computed as the ratio of the outbound energy to the inbound energy, summing all incoming pulses or fraction of pulses per voxel. Local Plant Area Density (PAD) was then computed for each voxel from the local transmittance values by applying Beer-Lambert's turbid medium approximation, assuming isotropic transmittance (Vincent et al. 2015; Musselman et al. 2013; Parker et al. 2001). Missing data (un-sampled voxels) were filled in through local neighbourhood averaging. Vertical integration of PAD gives the Plant Area Index (PAI), which contrary to the Leaf Area Index (LAI) considers all vegetation components, including woody structural parts (Vincent et al. 2015; Bréda 2003; Pocewicz et al. 2004). The estimates of mean PAI for Itoupé, Nouragues and Paracou are given in **Table 4**.

The radiative transfer modelling was performed using version 5.6.2 of DART. DART is “one of the most comprehensive physically based 3D models simulating the Earth-atmosphere radiation interaction from visible to thermal infrared wavelengths” (Gastellu-Etchegorry et al. 2015). It allows for realistic simulation of the reflectance of the canopy by tracing how light passes through and interacts with the vegetation structure, with that structural information provided via the 3D mock-ups generated by AMAPvox (Gastellu-Etchegorry et al. 2015; Vincent et al. 2015). In addition to the vegetation structure information, the illumination source for the radiative transfer modelling was provided via data acquired from the solar position calculator, allowing for simulating reflectance at specific periods of time.

DART simulations were based on the hypothesis that the only factor varying throughout time was the solar position, with the exception of the runs in which the PAI of the plots were also modified. In total, 15 sets of DART runs were elaborated, totalling 151 individual simulations (see **Table 5**). While monthly modelling was done for all three sites, diurnal radiative transfer modelling focused solely on the Paracou plot. In terms of the DART configuration, for each simulation, blue, green, red, and near-infrared (NIR) surface reflectance at nadir were estimated by DART, using the relative spectral response (RSR) function of the MODIS sensors to allow for comparison of the simulations' derivatives with the MODIS surface reflectance data acquired. The model runs covered three specific time-scales: a single instant (e.g. 12:30pm on 15 September), a day (discretized into 13 time-steps across a ~12-hour window during the daytime), and a year (discretized into 12 monthly time-steps across the year), with the latter two allowing for evaluation of the 'behaviour' of EVI over the corresponding periods.

In terms of modelling intra-annual (monthly) variation in EVI, simulations were run to estimate reflectance at solar noon on the approximate mid-point of each month, allowing for characterization of the pattern in EVI across the year as solar elevation changes at solar noon.

It should be noted that solar noon was chosen in order to compare that data with the MODIS reflectance data which was itself estimated based on solar noon (C. Schaaf, Liu, and Gao 2006). For further characterization of the variation in EVI on a finer temporal scale, simulations were also conducted to examine the impact of the hourly variation of solar elevation and solar azimuth (for a total of 13 time-steps). Those simulations focused only on the mid-points of two specific months, September and December, the respective months with the highest and the lowest variation in solar elevation, and corresponding to the dry and wet seasons.

For the 15 September run, the impact of varying leaf angle distribution (LAD) on EVI was also assessed, as it is known that surface reflectance estimates are influenced by LAD (Ross 1981; Wang et al. 2007; Pisek et al. 2013; Raabe et al. 2015). This assessment was done by modelling reflectance using the erectophile, plagiophile, and planophile LADs, complementing the standard spherical distribution used in most of the other runs. With an erectophile LAD, the leaves are mostly oriented horizontally, which is the opposite distribution to the planophile LAD in which leaves are mostly oriented vertically (Ross 1981; Raabe et al. 2015). In contrast, in the plagiophile LAD, slanted leaves are most common (Ross 1981; Raabe et al. 2015). With a spherical LAD, the leaves are oriented spherically, and where leaf distribution is unknown, spherical LAD is usually assumed (Pisek et al. 2013). Choice of the erectophile LAD, for instance, allowed for simulating how the vegetation canopy might appear under drought stress, while use of the planophile distribution allowed for simulation of a canopy with trees seeking to maximize the amount of light absorption (Ross 1981; Raabe et al. 2015). Use of the plagiophile LAD allowed for a compromise between the planophile and erectophile LADs.

Additionally, to test the alternative hypothesis that phenological variation does drive the variation in EVI, a set of simulations were conducted using a range of PAI values which had been patterned off of the variation of MODIS-derived LAI. The monthly percent change in MODIS LAI was estimated and then applied to the PAI values, leading to a range of PAI values from 9.7 to 13.3. Those changes in PAI were then applied globally to the Paracou plot. It should also be mentioned that PAI was modified in place of LAI because of the limitations in directly deriving LAI from ALS data, i.e. PAI can readily be derived, whereas currently LAI cannot be. Both PAI and LAI can be considered as proxies for the overall vegetation density. Variation of the PAI values allowed for understanding how EVI varies based on the interaction of both solar elevation variation and PAI variation (i.e. phenology). For Paracou, reflectance at the instant of 12:30pm on 15 September was modelled via the modification of both LAD and PAI, focusing on PAI values of 50%, 75% and 100% of the AMAPvox-derived estimate. That allowed for assessing the sensitivity of EVI to combined changes in LAD and PAI.

Statistical analyses

From the reflectance data generated from each individual DART run, EVI was generated using the standard algorithm (Huete and Justice 1999) which utilizes blue, red, and NIR reflectance, in combination with a sensor-specific gain factor (G), coefficients ($C1$, $C2$) and a canopy background adjustment factor, L . The equation is given as follows, and the coefficients used pertain to those of the MODIS sensor, where the gain factor G is equal to 2.5, the canopy background adjustment factor L is equal to 1, and the aerosol resistance coefficients $C1$ and $C2$ are respectively equal to 6 and 7.5 (Huete and Justice 1999):

$$\text{EVI} = G \times \frac{(\text{NIR} - \text{red})}{(\text{NIR} + C1 \times \text{red} - C2 \times \text{blue} + L)}$$

Following the radiative transfer modelling and the extraction of satellite-derived estimates of EVI, AOD, and LAI, statistical analyses were performed to (a) assess correlations among the modelled reflectance outputs themselves, and (b) assess correlations between the modelled outputs and the satellite-derived data. Specifically, correlation analyses (using the Pearson product-moment correlation coefficient, Pearson's *r*) were performed to identify the degree to which the model-derived EVI corresponded between the different sites, as well as the degree to which the model-derived EVI corresponded with the satellite-derived EVI, following the analysis strategy elaborated in **Figure 10**. The correlation analyses were done using the correlation function and the CORRPLOT package in R (Wei and Simko 2016; R Foundation 2011).

Table 5. Details of radiative transfer simulations run using DART (PAI and LAD refer to Plant Area Index and Leaf Angle Distribution parameters in DART.)

No.	Period	Times	# time steps	Site	Solar azimuth	Solar elev.	PAI	LAD
1	1 min.	12:30	1	Paracou	288°	2.4°	6.7-13.3	erectophile
2	1 min.	12:30	1	Paracou	288°	2.4°	6.7-13.3	plagiophile
3	1 min.	12:30	1	Paracou	288°	2.4°	6.7-13.3	planophile
4	1 min.	12:30	1	Paracou	288°	2.4°	6.7-13.3	spherical
5	1 day (15/09)	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	13.3	erectophile
6	15/09	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	13.3	plagiophile
7	15/09	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	13.3	planophile
8	15/09	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	13.3	spherical
9	15/09	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	6.7	spherical
10	15/09	6:30-18:30	13	Paracou	0 - 360°	0.1-87.6°	9.98	spherical
11	15/12	6:34-18:20	13	Paracou	0 - 360°	0.1-61.4°	13.3	spherical
12	1 year	solar noon	12	Itoupé	0° , 180°	61.5-87.7°	10.8	spherical
13	1 year	solar noon	12	Nouragues	0° , 180°	61.5-87.7°	13.2	spherical
14	1 year	solar noon	12	Paracou	0° , 180°	61.5-87.7°	13.3	spherical
15	1 year	solar noon	12	Paracou	0° , 180°	61.5-87.7°	9.7-13.3	spherical

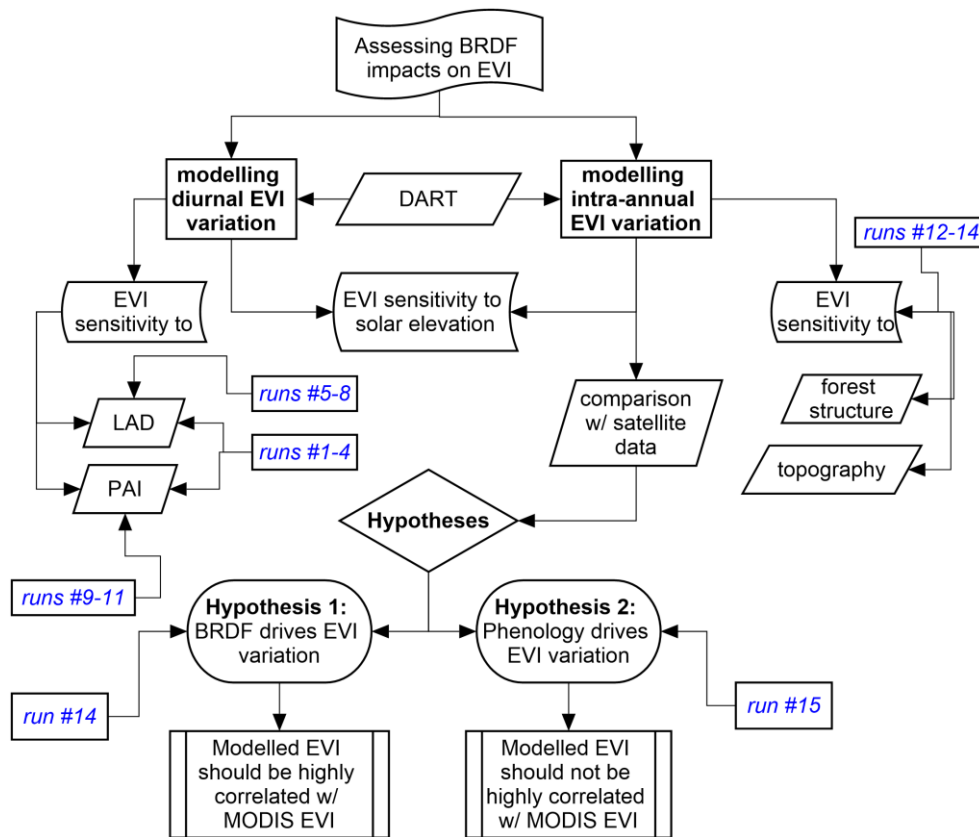


Figure 10. Overall modelling and analysis strategy; model run numbers refer to the sets of runs referred to in **Table 5**.

iii. Assessing seasonal variation of vegetation indices by forest type

Complementary to the assessments of BRDF on vegetation index data at the plot and regional scale, analyses were also carried out at an intermediate scale between the two, to assess the patterns of VI variation in data already corrected for BRDF. This addressed the fifth research question regarding seasonal temporal patterns in tropical forests. As with the other analyses, data from both MODIS and VGT were selected as the principal inputs for this study.

To reduce potential data volume and to follow in the steps of earlier studies, vegetation indices from the 2 sensors were selected (listed in **Table 6**). These included the EVI, the fraction of green vegetation cover (FCOVER), and the Leaf Area Index (LAI). While each index serves as a proxy for photosynthetic activity, the indices differ greatly in what they are supposed to estimate. EVI is designed to “quantify the ‘green’ vegetation signal across a global range of vegetation conditions while minimizing canopy influences associated with intimate mixing by non-vegetation related signals” (Huete et al. 1999). FCOVER is described as “the fraction of green vegetation covering a unit area of horizontal soil [...] correspond[ing] to the gap fraction in the nadir direction,” and “a very good candidate for substitution of classical vegetation indices” (Camacho et al. 1999). Lastly, LAI “is defined as half the developed area of photosynthetically active elements of the vegetation per unit horizontal ground area” (Baret & Weiss 2014).

Table 6. Vegetation indices used in this study.

No.	Index	Product	Source	Period
1	EVI	MCD43B4-derived	MODIS	July 2002-present
2	LAI	MCD15A2		
3	FCOVER	V1	VGT	Dec. 1998-Apr. 2014
4	LAI	V1		

MODIS and VGT have provided in excess of 15 years of data to date, via the presence of twin MODIS sensors on the Aqua and Terra platforms, and twin VGT instruments on the now-defunct SPOT-4 and SPOT-5 satellites (Lillesand et al. 2007). However, to ensure comparability between the MODIS- and VGT-derived data, only data corresponding to the temporal overlap between the sensors was used. That corresponded to the almost 12 year period spanning July 2002 (following the launch of MODIS Aqua) through March 2014 (just prior to SPOT-5's end of mission). The data represented acquisitions from approximately 4,292 days, but which were analyzed in terms of the 141 constituent months, facilitating the handling of a large volume of data. Also, the MCD43B4 data were resampled from 500m spatial resolution to match the, 1 km resolution of the other datasets.

Reflectance data assembly

While the VGT data was already readily available in the form of pre-processed indices (i.e. FCOVER, LAI), in the case of MODIS, the EVI data had to be derived from the raw reflectance data. Nadir BRDF-corrected reflectance estimates from MODIS (the MCD43B4 product, collection 5) for French Guiana (tile h12v08 in the MODIS reference system) were acquired for the period indicated. MCD43B4 is based on reflectance estimates from both MODIS Aqua and MODIS Terra, and the quality is considered better than products derived from only a single satellite. Data were filtered using the quality assessment-quality control (QA/QC) data from the corresponding MCD43B2 dataset, whose archive had also been acquired. Quality of the input data was assured by selection of only "best quality, full inversion" reflectance data (Schaaf et al. 2002).

Since the MCD43B4 data was available as 424 overlapping 16-day datasets (and not as monthly data), that data was 'compressed' into monthly data: (i) the 141-month archive, and (ii) a compressed 12-month archive representing mean monthly reflectances over a calendar year. For instance, in the latter case, mean September reflectance would refer to the reflectance averaged from September data for all the years analyzed (i.e. 2002-2013). To reduce noise in the latter dataset, the monthly means were extracted by taking the minimum reflectance for each 16 day period for all spectral bands, with the exception of the near infrared band, from which the maximum reflectance was extracted to remove noise, following an approach presented in an earlier study (Hansen et al. 2003). This was done because in most spectral bands, aerosols increase spectral reflectance, but in the near-infrared band, the effect is the opposite (Kaufman et al. 1992; Jensen 2006).

Vegetation index extraction

EVI was extracted from the monthly MCD43B4 reflectance data using the blue, red, and near-infrared bands. MODIS LAI data were also extracted from the MCD15A2 product, an 8-day product also using observations from both MODIS instruments. For the MCD15A2 data, quality assessment flags were used to ensure the extraction of only the highest quality observations. To allow for comparison with the earlier French Guiana satellite-based phenology study, EVI data from the MOD13A2 product was also extracted, for the time-period considered (Pennec et al. 2011). This study examined VI variation across 5 forest types mapped via unsupervised classification. The MOD13A2 data included here would thus be equivalent to agglomerating the VI trends from those 5 types, and is thus in essence a recreation of the data from Pennec et al. (2011). Data from all sources were originally acquired at the scale of the Guiana Shield and subsequently subset to French Guiana. Additional filtering to derive monthly data was unnecessary for the VGT-derived FCOVER and LAI data, as the data already represent 30-day observations. To limit the analysis to forest, data from other vegetation types was masked out, using a forest mask derived from unsupervised classification of MCD43 reflectance data. The mask was similar to the approach used in the earlier study (Pennec et al. 2011).

Statistical analyses were done to determine (i) whether there were statistically significant differences between monthly VI estimates (using the Kruskal-Wallis multiple comparison test), and (ii) the extent to which the different VIs were correlated to each other (using the Pearson product-moment correlation coefficient). With the Kruskal-Wallis test, pair-wise comparisons of the mean monthly VI estimates were done to determine whether or not the differences between monthly values were significant (Pohlert 2014).

Multi-scale analyses

It was noted that territorial-level variation in VI estimates might not necessarily apply to finer spatial scales. Data were therefore analyzed for 4 dispersed, smaller sites (**Figure 11**). These were: (i) the mangroves of the Marécages de Kaw in northeast French Guiana (439 km²), (ii) the mixed forest in Montagne Plomb in north-central French Guiana (122 km²), (iii) the Parinari-dominated forests near the Waki River in south-central French Guiana (85 km²), and (iv) the mixed low forest area near the Arawa mountains, also in south-central French Guiana (23 km²). Where the unsupervised classification indicates that French Guiana's forest cover is approximately 82,100 km² (approx. 98% forest cover), the 4 sites represent only 0.81% of the territory's total forest area. A data subset was extracted for each site, and the 4 data subsets were analyzed.

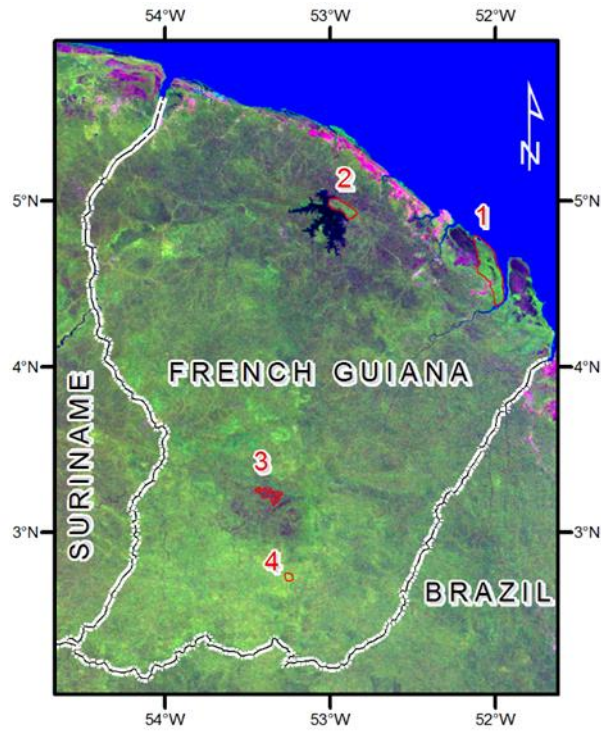


Figure 11. MCD43B4-derived September reflectance for French Guiana (12-year average), and location of 4 study sites (1: Kaw, 2: Montagne Plomb, 3: Waki, 4: Arawa).

IV. Examining patterns of spatio-temporal variation for forest type mapping

In the final part of this thesis, the insights gained from the spatial and the temporal analyses were used to address the sixth and final research question in seeking how to exploit combined spatio-temporal data for ecologically consistent characterization of forest types. The overall work flow of for that part of this thesis is presented in **Figure 12**, and essentially consisted of four phases: (i) assembling a robust VI time-series, (ii) extraction of the seasonal pattern from that time-series, (iii) mapping forests based on the dominant spatio-temporal patterns, and (iv) relating the spatial variation in the extracted seasonal pattern to environmental gradients, both climatic and topographic.

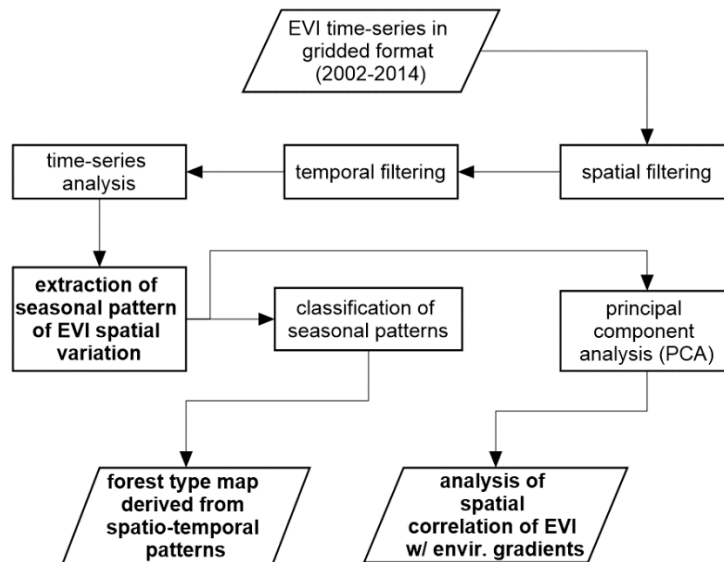


Figure 12. Work flow for the generation of forest type maps from VI time series and for analysing the correlation between EVI spatial patterns and environmental gradients.

Assembly of a VI time-series

As a precursor to the time-series analysis, large time-series archives were assembled from the 5 indices indicated in **Table 7** (i.e. EVI, FAPAR, FCOVER, LAI, and NDVI). In terms of the MODIS-derived datasets, monthly EVI and NDVI estimates were derived from the 16-day BRDF-corrected MCD43A4 dataset (ref), while FAPAR and LAI were derived from the 4-day MCD15A3 dataset, all of which were acquired from the publicly accessible NASA Reverb portal (<http://reverb.echo.nasa.gov>). The VGT-derived datasets did not require additional processing and were acquired from the publicly accessible Copernicus Global Land Service portal (<http://land.copernicus.vgt.vito.be/PDF/portal/Application.html>).

In order to focus the analysis on a single VI, a feasibility assessment was conducted, focusing on factors such as the degree of cloud-free observations available per dataset, the temporal resolution, spatial resolution, and the degree of spatial acuity of each index. On the basis of that assessment, it was decided to focus the analysis on EVI, mainly because these products possessed the lowest degree of cloud cover relative to other VI sources, likely due to the availability of twice daily observations, compared to VGT's only once-daily observations. The spatial resolution of the EVI data was another compelling factor. The spatial resolution of MODIS EVI (463m) would allow for the mapping of forests at an approximate spatial scale of 21.4 hectares per pixel. While the MODIS EVI archive extends from March 2000 to present, to capitalize on the availability of both MODIS Terra (March 2000-present) and MODIS Aqua (July 2002-present), the window for the time-series archive was limited to the 12-year period between January 2003 and December 2014.

Time-series analysis and generation of forest type maps from extracted seasonal pattern data

While the MODIS EVI (and the MODIS NDVI) time-series possessed a lower degree of cloud cover than the other indices, the data were not completely without gaps caused by cloud cover. It was likewise noted for the different VIs that on the edges of data gaps, pixel values were generally lower, possibly indicating the presence of unfiltered cloud shadows. A 3x3 median filter was applied to each of the 144 months in the EVI time-series, which aided in filling the data gaps, but not completely. This also aided in ameliorating somewhat the effect of the cloud residual shadows. Following this, the monthly data coverage was evaluated, and it was noted that the application of the 3x3 median filter resulted in each 463m pixel having at least one valid value across each of the 12 months. That was an important condition for the application of the time-series analysis.

Following the assembly of the spatially-filtered 144-month EVI archive, temporal filtering was done using the Savitzky-Golay filter from the signal package R (Crawley 2013). This temporal filtering was done to temporally smooth the data, assuming that some peaks and lows in the time-series are anomalous (e.g. caused by clouds or cloud shadows). This is a similar technique to the one used by (Tan et al. 2011). Temporal filtering was done using a 3-month (i.e. 1 month forward and 1 month backward) window and a 2nd degree polynomial which in general did not over-smooth the time-series. Following this, using a modification of the Loess seasonal decomposition method in R (STL package), on a pixel-by-pixel basis, the seasonal (monthly) spatial pattern of EVI was extracted (Crawley 2013), also mirroring the approach of an earlier study (Huesca et al. 2015).

The monthly EVI spatial pattern data constituted a major output of this study, allowing for analysing and visualising how French Guiana's forests' spectral response (as estimated by EVI) varies in both space and time. That data were then used as an input to an unsupervised clustering approach using the ISODATA algorithm (Ball and Hall 1965). The five classes representing the most dominant patterns of phenological variation were thus mapped as individual forest types.

Principal component analysis (PCA) and assessment of spatial variation in EVI

As part of understanding how the spatial variation in EVI is influenced by environmental gradients (climatic and topographic), the extracted EVI seasonal pattern data were then analysed using principal component analysis (PCA). As PCA re-orders data and then concentrates variation within the first few axes (Griffith 2012; Crawley 2013), selection of individual PCA axes allowed for understanding the main patterns of both spatial and temporal variation in EVI. In this case, over 90% of the variation in EVI was represented by the first axis of the PCA.

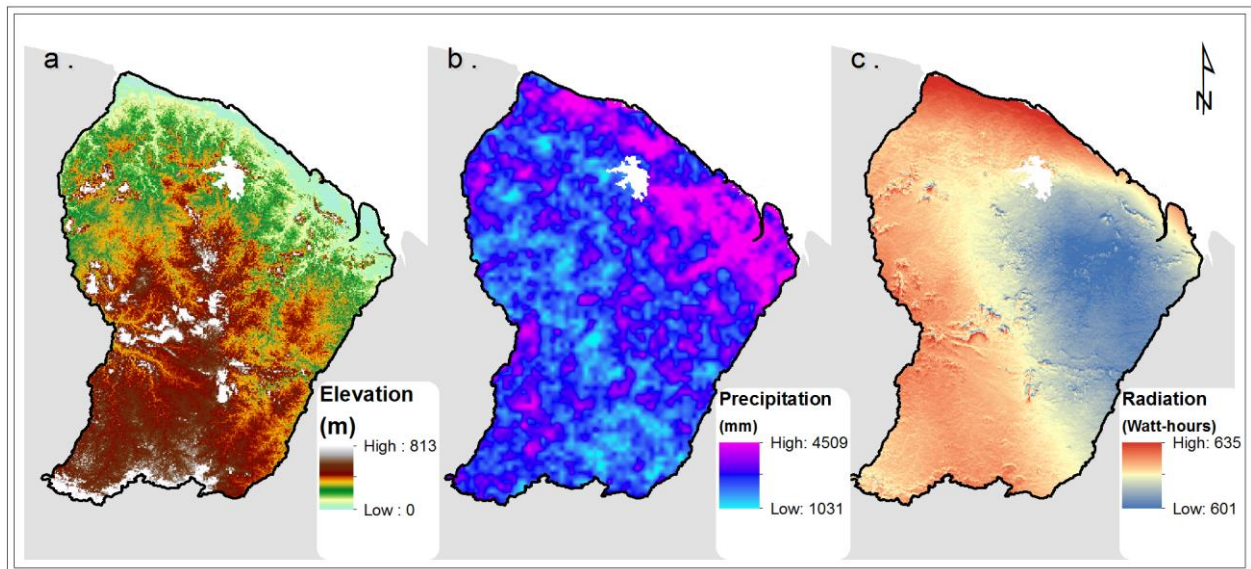


Figure 13. Environmental gradients extracted for French Guiana: (a) elevation (derived from the SRTM digital elevation model), (b) mean annual precipitation (derived from TRMM 2B31 product), and (c) mean monthly total radiation (modelled using CERES net total flux data).

The PCA data were used as inputs (as the dependent variable) in Ordinary Least Squares (OLS) regression against ten (10) environmental gradients (see **Figure 13** and **Table 7**) as a means of assessing how the spatial variation of VIs could be explained by environmental gradients. Via the OLS regression, the spatial variation of EVI was modelled as a function of the combined spatial variation of cloud cover, evapotranspiration, precipitation, long wave radiation, shortwave radiation, total radiation, elevation, topographic slope, and potential flow accumulation. A complete model using all of the variables was assessed, as well as sub-models assessing the effects of only climatic variation and topographic variation:

Model 1 (complete): $EVI_i = \beta_0 + \beta_1 \text{Cloud cover}_i + \beta_2 \text{ET0}_i + \beta_3 \text{Precipitation}_i + \beta_4 \text{LW radiation}_i + \beta_5 \text{SW radiation}_i + \beta_6 \text{total radiation}_i + \beta_7 \text{Elevation}_i + \beta_8 \text{Geomorphology}_i + \beta_9 \text{Slope}_i + \beta_{10} \text{Flow accumulation}_i + \varepsilon_i$

Model 2 (climatic): $EVI_i = \beta_0 + \beta_1 \text{Cloud cover}_i + \beta_2 \text{ET0}_i + \beta_3 \text{Precipitation}_i + \beta_4 \text{LW radiation}_i + \beta_5 \text{SW radiation}_i + \beta_6 \text{total radiation}_i + \varepsilon_i$

Model 3 (topographic): $EVI_i = \beta_0 + \beta_1 \text{Elevation}_i + \beta_2 \text{Geomorphology}_i + \beta_3 \text{Slope}_i + \beta_4 \text{Flow accumulation}_i + \varepsilon_i$

Variance partitioning was also performed to determine the degree to which EVI spatially co-varied with either the climate's spatial variation or the spatial variation of the topography. This partly mirrored the approach of an earlier study which examined how French Guiana's floristic composition spatially co-varied with selected environmental variables (Guitet et al. 2015).

Table 7. Environmental variables used in the OLS regression of spatial variation of the different vegetation indices.

No.	Variable	Classification	Source
1	Cloud cover, total annual	Climatic	MODIS11A2-derived
2	Reference evapotranspiration (ET ₀), mean monthly		Derived from MODIS11A2 and TRMM 2B31
3	Precipitation, total annual		TRMM 2B31
4	Long wave radiation, total annual		CERES-derived
5	Short wave radiation, total annual		CERES-derived
6	Total radiation, mean monthly		Derived from CERES net total flux and SRTM elevation
7	Elevation	Topographic	SRTM
8	Flow accumulation		SRTM-derived
9	Geomorphology		S. Guitet et al. 2015
10	Topographic slope		SRTM-derived

Chapter 1: Spatial variation of tropical forests

Overview of the chapter

This Chapter focuses on the spatial variation of tropical forests and specifically addresses the following research questions:

- i. How do bi-directional effects affect the spatial variation of spectral response of tropical forests, and how do they affect the spatial variation of estimated distributions of forest types?
- ii. How do estimated spatial distributions of forest types change seasonally?

In thus addressing the spatial variation of tropical forests, the first part of the chapter addresses how artefacts related to sun-sensor geometry affect observations of light reflected from forests, which are in turn used to identify different types of forests. This is followed up by an examination of how the mapping of the spatial variation of tropical forests from such imagery is in turn impacted by image artefacts. The results presented are based on an oral presentation presented in May 2016 at the European Space Agency's 2016 Living Planet Symposium in Prague, Czech Republic (Cherrington et al. 2016a). Lastly, the other part of the chapter explores how forest canopy reflectance changes month-to-month, and the implications of variation. Those findings are reproduced in part from a conference paper published in the proceedings of the XIV World Forestry Congress, held in September 2015 in Durban, South Africa (Cherrington et al. 2015a).

Introduction

Characterization of the spatial patterns of variation of tropical forests remains a major focus of ecology and is also the main focus of this Chapter. As will be explored here, instrumental artefacts represent a significant obstacle to using remote sensing to characterize those patterns of spatial variation. For instance, data from the Landsat series of satellites are recognized as the workhorses of remote sensing studies related to the monitoring of tropical forests (Hansen and Loveland 2012). The existence of a 40+ year archive of satellite data from Landsat, and of global coverage, has allowed for mapping forests across large, otherwise inaccessible landscapes. In terms of the state of the art in forest mapping, much attention has been paid to the discrimination of forests versus non-forest areas, even as the onus is on mapping the spatial heterogeneity of forest types across the globe. Such data on forest types constitute key inputs to efforts ranging from biodiversity conservation to forest management to climate change mitigation. Regarding the latter, for instance, it is known that "carbon stocks vary by forest type... [with] tropical pine forests [having] a different stock than tropical broadleaf forests which will again have different stock than woodlands or mangrove forests" (GOF-C-GOLD 2012). Nevertheless, identifying forest types using data sources such as Landsat, presents methodological obstacles which may not necessarily be present when addressing only the differences in spectral response between forests and non-forested areas.

While analysts using Landsat have generally considered the Landsat satellites' sensors as having small fields-of-view (FOV), those sensors actually have an approximate FOV of 15 degrees across-track (roughly east to west), as illustrated in **Figure 14** (Danaher, Wu, and Campbell 2001). While the differences in reflectance across track stemming from the FOV have largely been considered negligible (Nagol et al. 2015), a small number of studies have sought to shed light on how those differences in reflectance may ultimately affect applications of the reflectance estimates, such as in mapping and monitoring tropical forests (Toivonen et al. 2006; Hansen et al. 2008; Potapov et al. 2012; Muro et al. 2016).

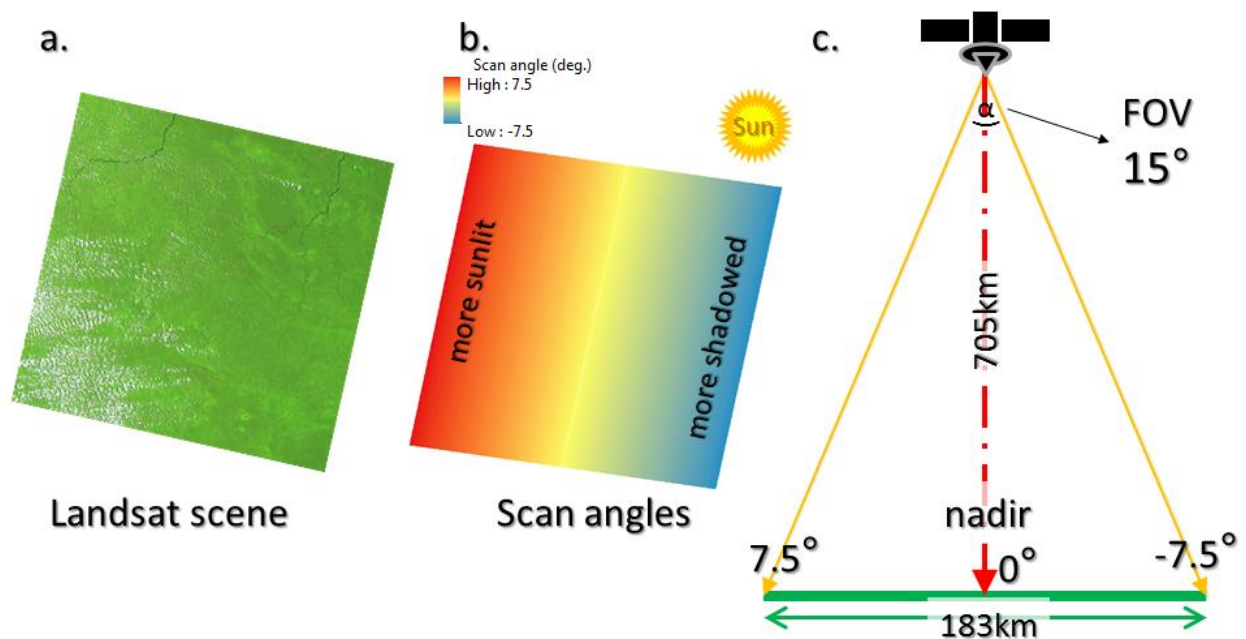


Figure 14. Effects of Landsat sensor viewing angles: a. Landsat scene in which view angle distortions are not readily visible; b. the corresponding scene scan angles, and c. the field of view (FOV) across the scene.

Those studies have noted a gradient in reflectance directly related to the sensor scan angle, a “sun-sensor geometry” effect also referred to as the bi-directional reflectance distribution function, BRDF (Nagol et al. 2015). Previously, much attention has been paid to how BRDF affects temporal variation / time-series extracted from satellite data (Morton et al. 2014; Soudani and François 2014; Hilker et al. 2014; Xu et al. 2015; Bi et al. 2015; Cherrington et al. 2015b; Wu et al. 2016; Lopes et al. 2016; Cherrington et al. 2016b). Conversely, not much attention has been focused on characterizing how BRDF affects the spatial variation of vegetation spectral response (Toivonen et al. 2006; Hansen et al. 2008; Potapov et al. 2012; Muro et al. 2016).

Those few studies note that the reflectance estimates from near the edges of the image swaths will possess distortions due to view angle (Nagol et al. 2015). Where the vegetation spectral response measured by Landsat’s sensors are used to distinguish types of forests or, more broadly, to distinguish forest from other land cover types, the implication from some of the aforementioned studies (e.g. Toivonen et al. 2006) is that the mapping of forests using

reflectance data affected by BRDF may ultimately result in the misidentification of forest types. Corrections therefore need to be done to remove across-track anisotropy in the reflectance estimates derived from Landsat data. Not correcting for such effects has been theorized to cause forest types surveyed using uncorrected data to be inaccurately mapped (Toivonen et al. 2006). However, at the level of large scale, satellite-based forest monitoring efforts, BRDF corrections have not been universally applied (Hansen and Loveland 2012).

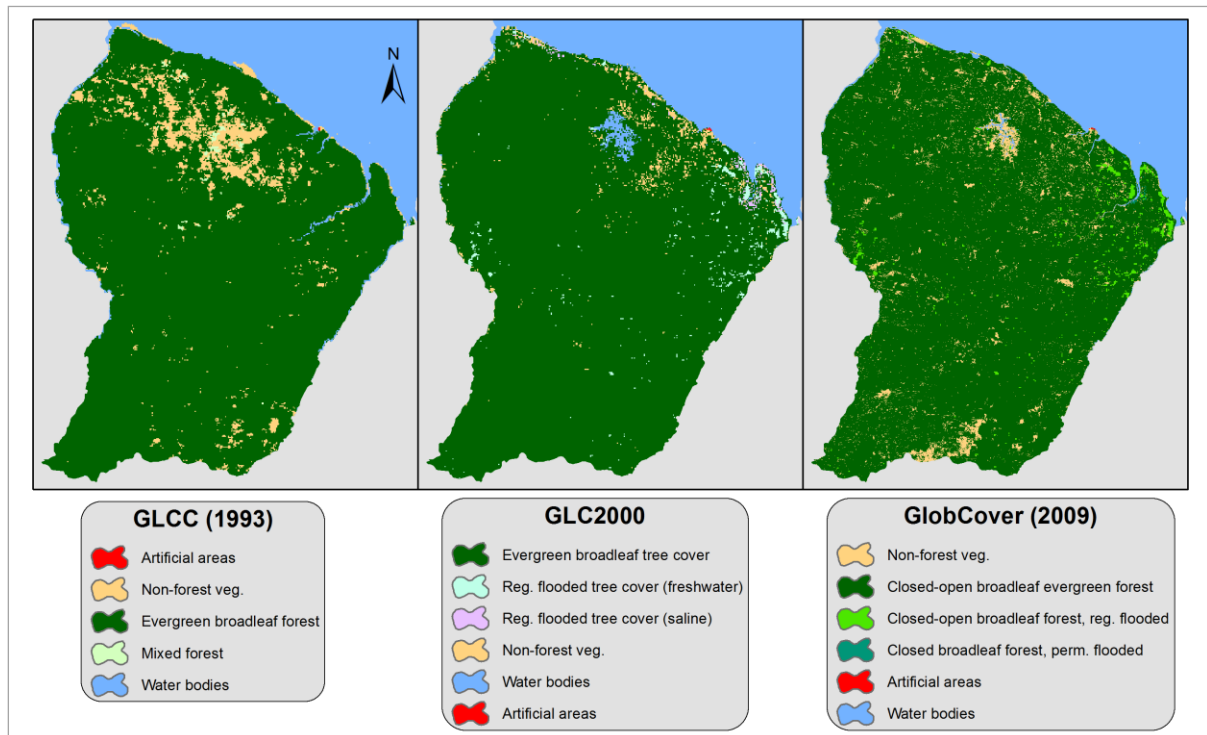


Figure 15. Land cover classifications of French Guiana (*with non-forest classes agglomerated*).

One area that would make an ideal case study for mapping forest types is French Guiana, an overseas Department of France which is highly forested and yet where there are only a handful of studies which have sought to characterize the spatial heterogeneity of the territory’s forest types (Girou 2001; Gond et al. 2011; Guitet, Brunaux, et al. 2015). Like other tropical forest territories, French Guiana suffers from the challenges of (i) perpetual heavy cloud cover, which adversely impact the ability to observe the forests during the entire annual cycle, and (ii) a territory covered by images from multiple satellite passes, making wall-to-wall mapping challenging. (However, *unlike* other territories, French Guiana has a historically low rate of land use change, as indicated by Hansen et al. 2013.) While the territory’s vegetation has been mapped in a number of global efforts (i.e. the 1993 Global Land Cover Characterization, Global Land Cover 2000, and GlobCover initiative of 2009), in such efforts, French Guiana has consistently been mapped as possessing a single, homogenous forest type. That gave rise to the coining of the term “green carpet” highlighting the failure of such efforts to distinguish the territory’s forest types (see **Figure 15**)¹.

¹ GlobCover indicates that French Guiana is covered by “closed to open broadleaved evergreen or semi-deciduous forest,” while the GLC2000 shows “broadleaved evergreen tree cover,” and the GLCC shows “evergreen broadleaf forest.” It should be noted that the classes mapped were inconsistent across the three efforts, leading to some differences between them.

Part I: BRDF impacts on reflectance and forest type mapping

Thus, as a first step toward using Landsat reflectance estimates for mapping of tropical forests, it is imperative to understand how BRDF actually impacts reflectance estimates. With forest type mapping as an eventual goal, the objective of this study was simply to determine the degree to which the vegetation spectral response estimates recorded by Landsat's sensors are affected by bi-directional effects. Related to this is the largely unresolved question as to whether such bi-directional effects will necessarily impact the ability to estimate forest type distributions (as such distributions are estimated from the reflectance data).

Part II: Seasonal variation of forest type distribution estimation

Parallel to that issue is the question of how the canopy-level spectral response patterns of tropical evergreen forest change seasonally (as observed in reflectance data already corrected for BRDF, such as that of the MODIS MCD43A4 product). Provided that the forests of French Guiana are evergreen, it was expected that the spectral response pattern (i.e. the spectral signatures) of each forest type should not vary significantly throughout the year, or at least it should vary minimally within a season. Furthermore, since the spatial distributions of forest types are estimated by mapping algorithms based on their spectral response patterns, it is expected that the resulting maps of spatial distributions of forest types should not show large variations of forest types during the year. In other words, for tropical evergreen forest, monthly reflectance data should indicate similar month-to-month spatial distributions of forest types. French Guiana thus serves as a case study for other tropical forest territories.

Results

I. BRDF impacts on reflectance

The comparison of the reflectance data with the Landsat sensor scan angles indicates that the reflectance is anisotropic across the scanning track, i.e. approximately east-west (see **Table 8**). Depending on the spectral band, the across-track reflectance differed by between 0.95% (in the case of the red reflectance) and 4.18% (in the case of the near infrared reflectance). And as indicated in **Figure 16**², when Landsat reflectance is linearly regressed against the scanning angle, the statistical relationship is also found to be high, ranging from a R^2 of 0.79 in the case of the red reflectance to 0.94 in the case of shortwave infrared reflectance (both Landsat bands 5 and 7). In contrast, analysis of the BRDF-corrected MODIS data generally indicate minimal across-track anisotropy, with the exception of band 3, which shows some anisotropy (see **Figure 17**).

² **Figures 16-18** only show the red through 2nd SWIR spectral bands of Landsat and MODIS and do not include the blue and green spectral bands. The bands shown are also considered the most important in terms of spectral classifications (Gond et al. 2011; Viennois et al. 2013).

Table 8. Landsat surface reflectance estimates at different scan angles, based on data acquired for orbits 227 and 228.

Landsat path	Spectral band	Reflectance			East-west reflectance difference	Reflectance change / unit scan angle increase
		at west edge (7.5°)	at nadir (0°)	at east edge (-7.5°)		
227 (central French Guiana)	1 (blue)	1.94%	0.81%	0.16%	1.78%	0.12%
	2 (green)	4.37%	2.62%	2.00%	2.36%	0.16%
	3 (red)	2.63%	1.58%	1.29%	1.35%	0.09%
	4 (near IR)	33.41%	31.12%	29.23%	4.18%	0.28%
	5 (SWIR1)	14.12%	13.21%	12.01%	2.11%	0.14%
	7 (SWIR2)	6.09%	5.01%	4.45%	1.64%	0.11%
228 (western French Guiana)	1 (blue)	1.82%	0.98%	0.33%	1.48%	0.10%
	2 (green)	3.87%	3.11%	2.47%	1.39%	0.09%
	3 (red)	2.64%	2.10%	1.68%	0.95%	0.06%
	4 (near IR)	27.44%	26.10%	24.15%	3.29%	0.22%
	5 (SWIR1)	13.25%	11.99%	10.92%	2.34%	0.16%
	7 (SWIR2)	5.35%	4.37%	3.80%	1.55%	0.10%

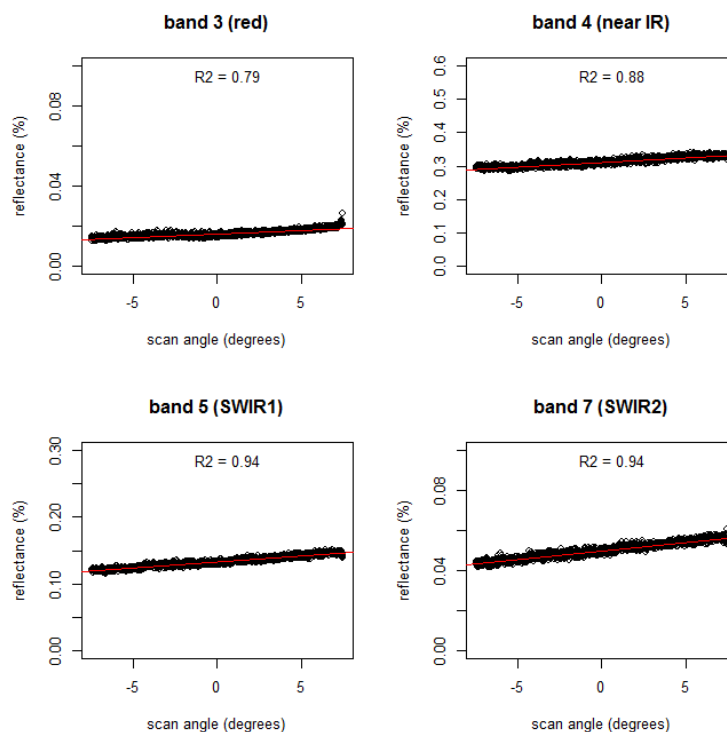


Figure 16. Landsat path 227 reflectance versus the sensor scan angle, with the red line showing the trend line for the regression of reflectance against scan angle and the R² indicating the fit of that regression.

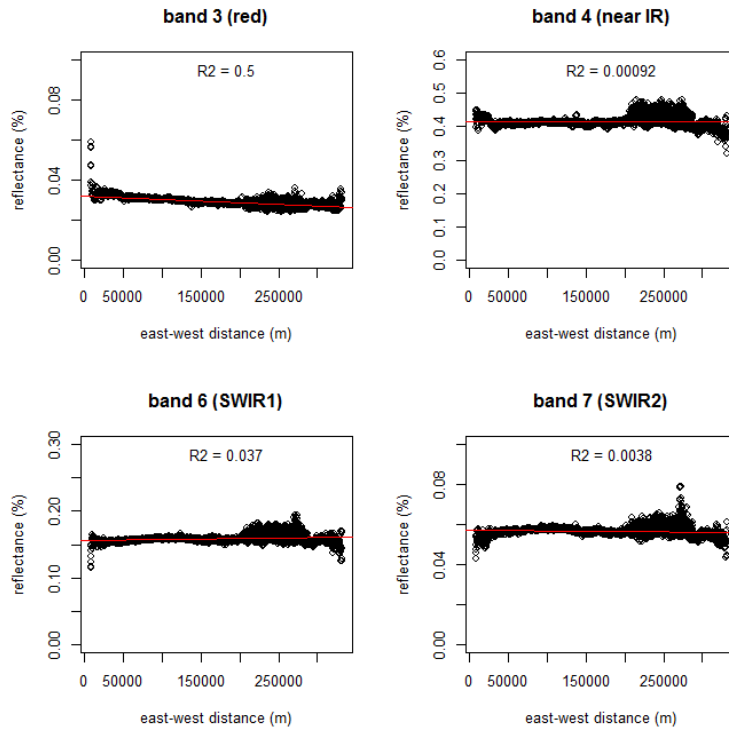


Figure 17. MODIS reflectance versus the sensor scan (as distance), with the red line showing the trend line for the regression of reflectance against scan angle and the R^2 indicating the fit of that regression; data are for the mean September MCD43A4 reflectance composite.

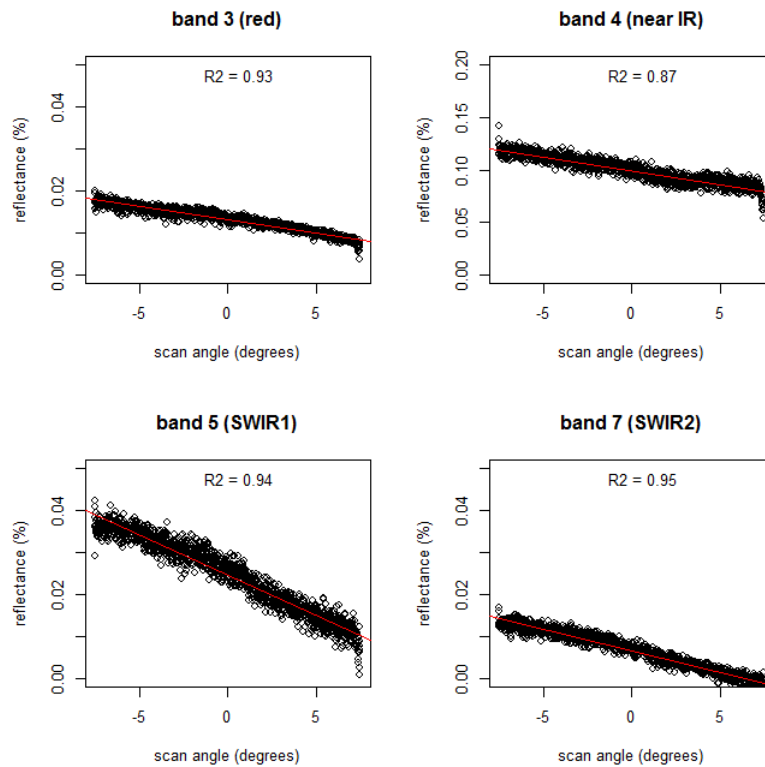


Figure 18. Landsat-MODIS reflectance bias versus the sensor scan angles (Landsat path 227), with the red line showing the trend line for the regression of the bias against scan angle and the R^2 indicating model fit.

Anisotropic reflectance could be noted directly in the Landsat surface reflectance estimates themselves (**Figure 16**) as well as in the comparison of that data with reference reflectance data which has been corrected for BRDF (**Figure 18**). In contrast to the lack of anisotropy in the BRDF-corrected MODIS reflectance reference dataset which was assembled, the Landsat-MODIS reflectance difference data likewise showed strong anisotropy across track, highly correlated with the Landsat scan angles (**Figure 18**). The spatial variation of those differences is illustrated in **Figure 19**. It should likewise be noted that the patterns shown in **Figure 16**, and **Figures 18-19** are congruent with each other. That is, the Landsat reflectance estimates are higher in the west where the forests *appear* sunlit (because of the viewing angle), and lower in the east where the forests *appear* shadowed. Hence, in **Figure 19**, differences between the MODIS reference reflectance data and the Landsat estimates are greatest in the east, where shadowing in Landsat would be greatest and shadowing in MODIS would be minimal due to the BRDF corrections.

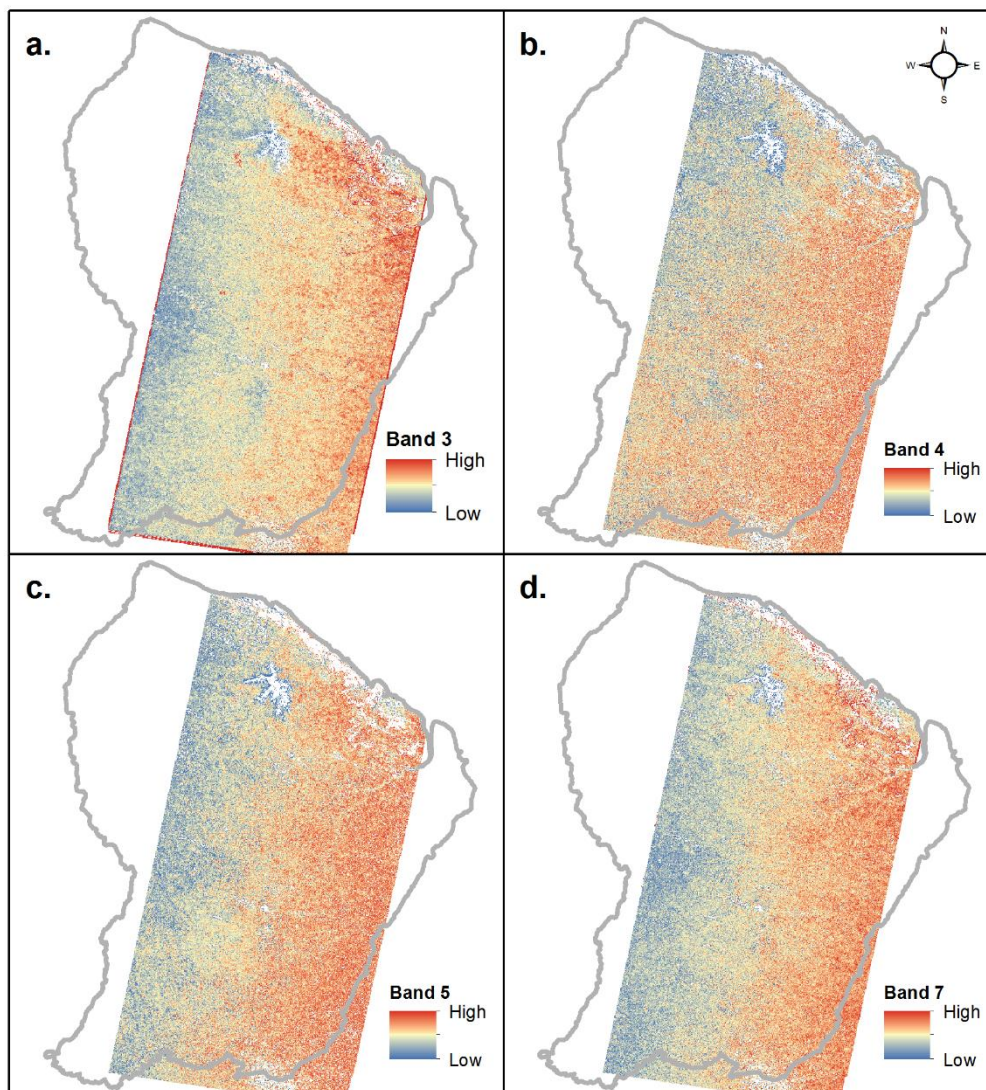


Figure 19. Landsat-MODIS reflectance bias for Landsat path 227 data from September 2005, compared to mean MCD43A4 reflectance for September.

II. BRDF impacts on forest type mapping

In terms of the differences between the two Landsat-derived forest type maps, the map derived from the image mosaic not corrected for BRDF impacts (**Figure 20c**) mirrored its source mosaic. That is, along the seams of where imagery from different orbits were mosaicked together, the forest type map had sharp distinctions between classes. In contrast, the forest cover map derived from imagery corrected for BRDF (**Figure 20d**) did not possess such sharp contrasts near the image seams.

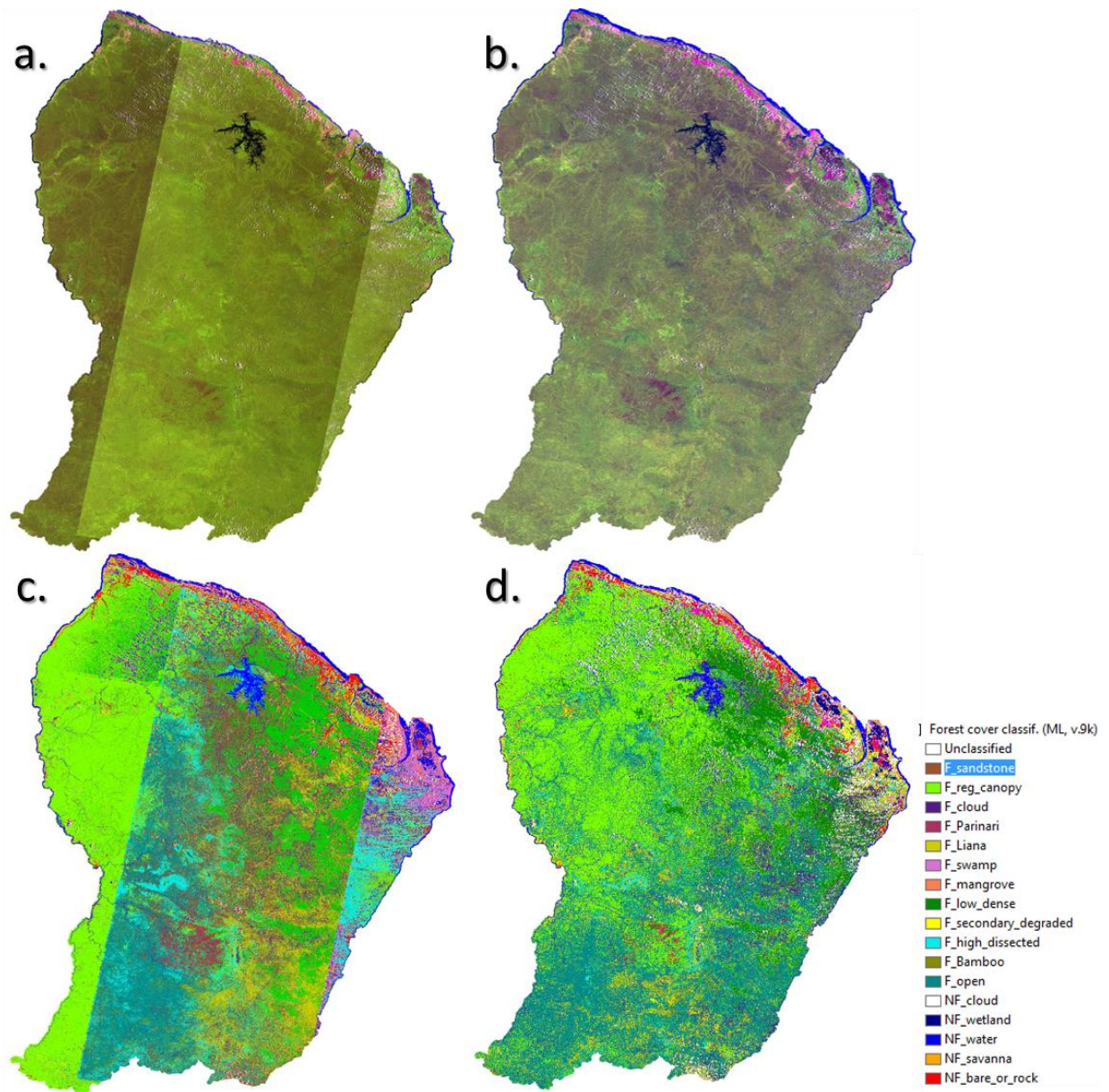


Figure 20. Landsat-derived surface reflectance estimates: not corrected for BRDF (top left), and corrected for BRDF (top right); forest type classifications: generated from reflectance data not corrected for BRDF (bottom left), and generated from BRDF-corrected data (bottom right).

Additionally, for the map derived from the uncorrected mosaic, it was apparent that the estimated distributions of forest types were greatly impacted by the sensor scan lines (**Figure 3**). As such, in **Figure 20c**, forests with regular canopies (shown in bright green) were shown to be localized mainly to the west of French Guiana, while in **Figure 20d**, the distribution is different. Additionally, in **Figure 20c**, forests with open canopies (shown in cyan) are shown to be located almost exclusively in the central-western part of the country, but stopping at the seam between two images, while in **Figure 20d**, the distribution of these forests is shown to extend to a more extensive area. Furthermore, in comparing **Figure 20c** and **Figure 20d**, analysis of the data indicates that the maps' pixels only match in 27.5% of the cases, indicating that the maps are 72.5% different.

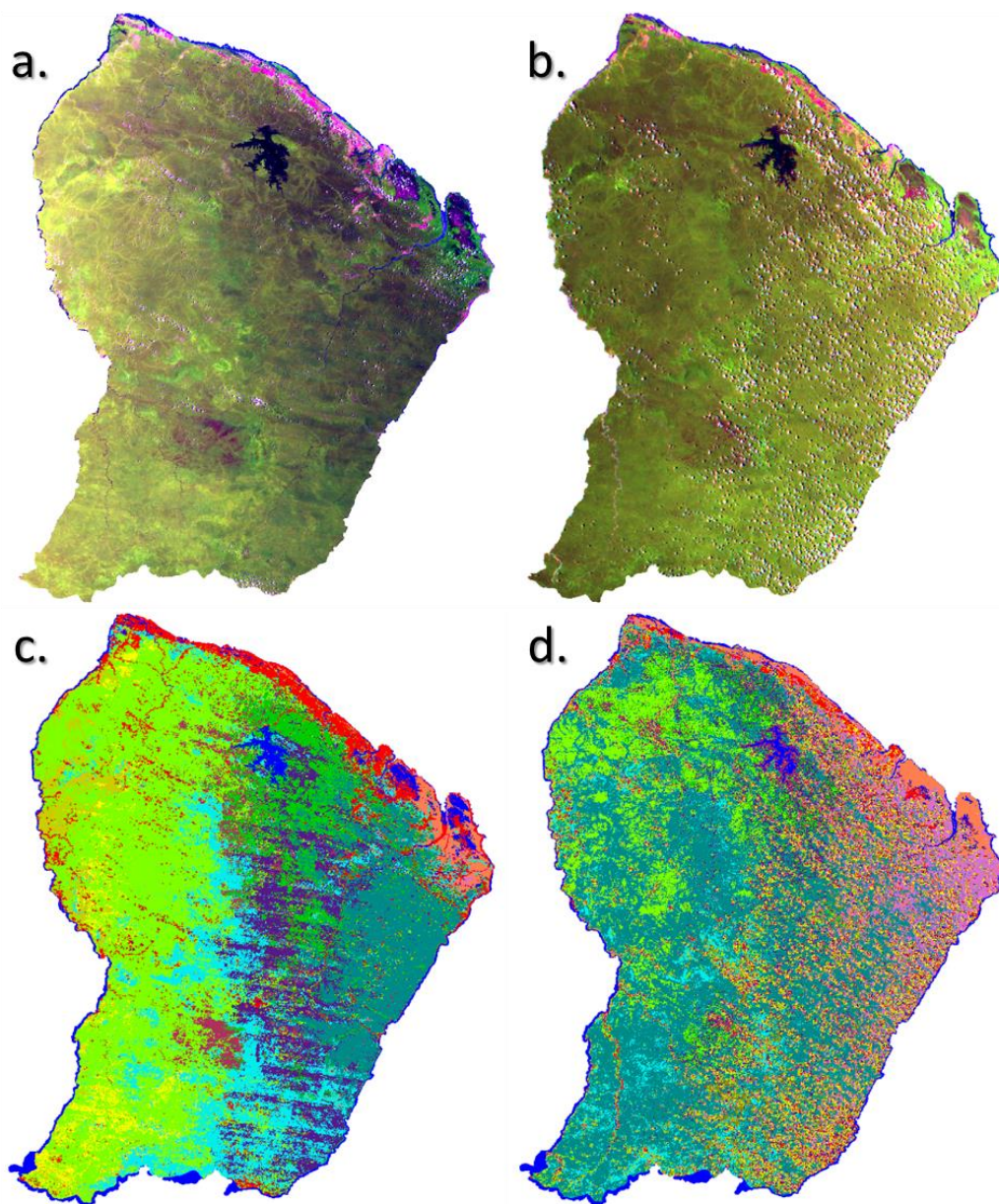


Figure 21. MODIS surface reflectance estimates for 27 September 2005: from ~10:30AM from MODIS Terra (top left), and from 1:30PM from MODIS Aqua (top right); forest type classifications: from the AM image (bottom left), and the PM image (bottom right); the legend is the same as in **Figure 20**.

Figure 21 provides an important contrast to **Figure 20**. While the source MODIS imagery depicted in Figure 4 were captured on the same date (27 September 2005) and around within about a half hour of the central column of Landsat-7 imagery in the mosaics depicted in **Figure 20**, as the MODIS data was collected off-nadir (at an angle), the resultant forest type maps display strong artefacts related to the path of the sensor scan. The produced maps (**Figure 21c** and **Figure 21d**) are extremely different, even as the source images were acquired within four hours of each other, changes in cloud cover notwithstanding. While the MODIS-derived maps differ greatly from the forest type map derived from the BRDF-corrected Landsat mosaic, certain patterns emerge in both **Figure 20d** and **Figure 21c**. For instance, both indicate the presence of low dense forests mainly in the area of and east of Montagne Plomb, the presence of forests with regular canopies mainly in the west, and the localization of *Parinari campestris*-dominated forests mainly near the Waki River in the south.

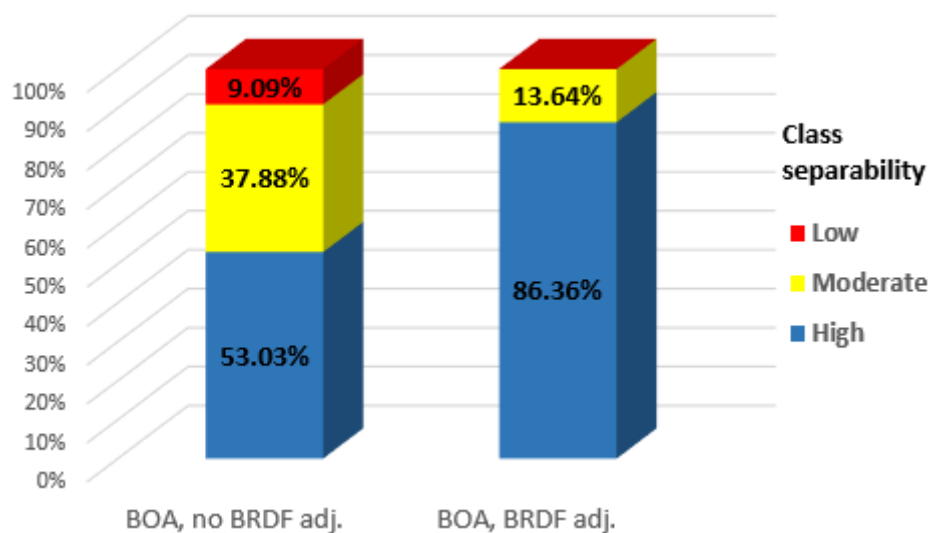


Figure 22. Separability of forest classes for Landsat reflectance data not corrected for BRDF (left), and Landsat reflectance data corrected for BRDF (right), based on the Jeffries-Matusita distance.

Further regarding comparison of the Landsat-derived forest type maps, **Figure 22** illustrates how the estimates of spectral separability of the forest types differed depending on the input imagery. What is shown is that the 12 types of forests are mostly determined to be spectrally distinct using the imagery which has been corrected for BRDF. On the other hand, in the imagery which was not corrected for BRDF, but merely corrected for atmospheric and topographic effects, only roughly half of the pairwise comparisons of forest types were indicated to be highly spectrally separable. For instance, using the uncorrected Landsat data, open canopy and dissected canopy forests were determined to be difficult to spectrally discriminate, but using the BRDF-corrected data, these were determined to be highly separable. Likewise, cloud forests were determined to be difficult to separate using the uncorrected data, but highly separable with the BRDF-corrected data.

III. Seasonal variation of forest type distribution estimates

As a subset of the forest distributions mapped, the forest types mapped using the mean August and September reflectance data are presented in **Figure 23**. While the forest types themselves do not constitute the principal focus of this study, it bears observing that the analyses indicates that different forest types are essentially confined to specific zones of French Guiana. For instance, forest type 1 (mangroves) are shown as confined to the coastal zone of the territory, while forest type 3 (forests dominated by *Parinari campestris*) are indicated to be present mainly in the area near the Waki River in southern French Guiana. Also related to the issue of how input data affects the discrimination of forest types, it can be observed that the two maps appear similar. However, only 41% of the pixels of the two maps actually coincide, meaning that between the two maps, 59% of the pixels are classified differently.

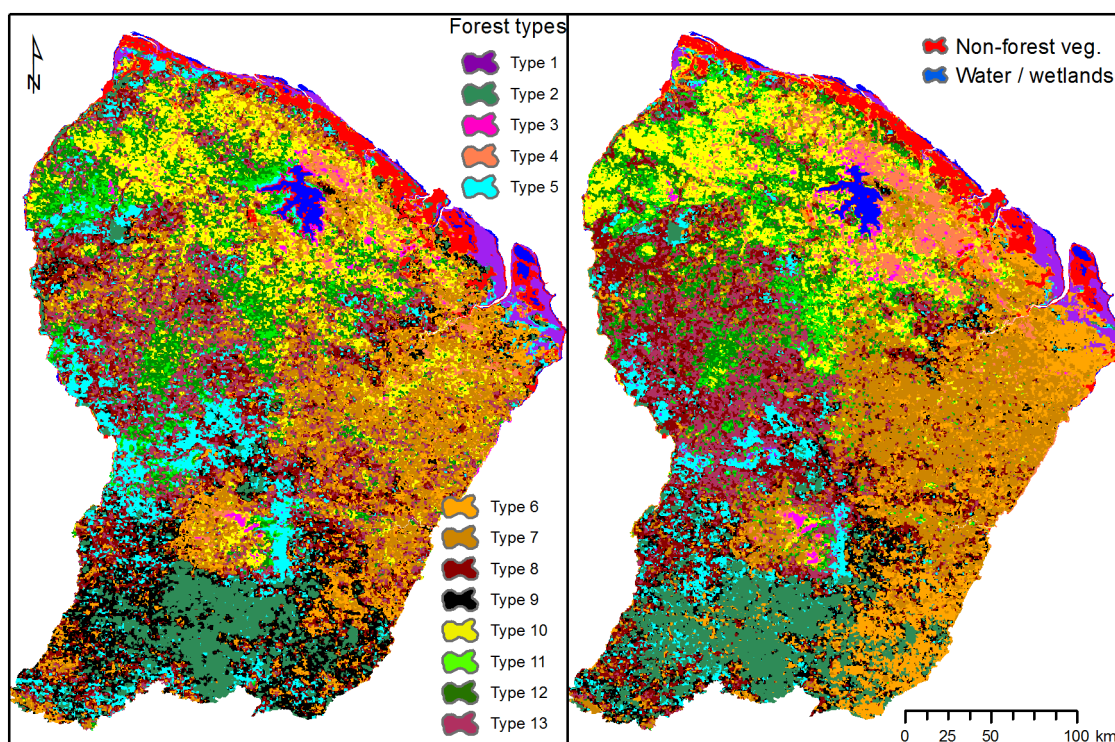


Figure 23. Maps of forest types, based on mean reflectance from August (left) and September (right).

In contrast to the mapping of forest types, **Figure 24** illustrates how the separability of forest types differs by month and by spectral bandwidth. When all 6 spectral bands are used, the forest types are 100% discriminable in August, as compared to less than 60% discriminable in September and October, less than 50% discriminable in July and November, and only 15.4% discriminable in December. In comparing the spectral subsets used, it can also be observed that use of the red, NIR, and 2 SWIR bands (bands 1267) yield overall better discrimination across almost all months than does the use of VNIR bands or only the 3-band combination of red, NIR, and SWIR (bands 126). Whether both SWIR bands are used, or only band 6, the forest types still remain highly discriminable in August (over 97% separability), as compared to the other months. Additionally, the separability of the forest types in the VNIR bands is lower

(85.9%) than the band combinations using the SWIR bands (97.4% and 98.7%). The lower separability of forest types in July, November, and December, may be partially explained by the estimate of spectral noise which is presented in **Figure 25**.

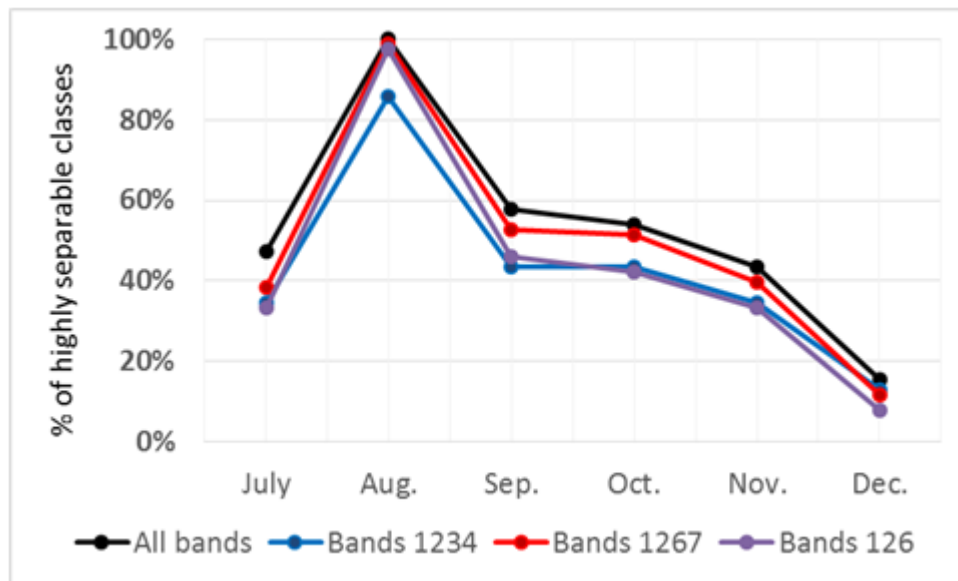


Figure 24. Monthly separability of forest classes, at different spectral resolutions.

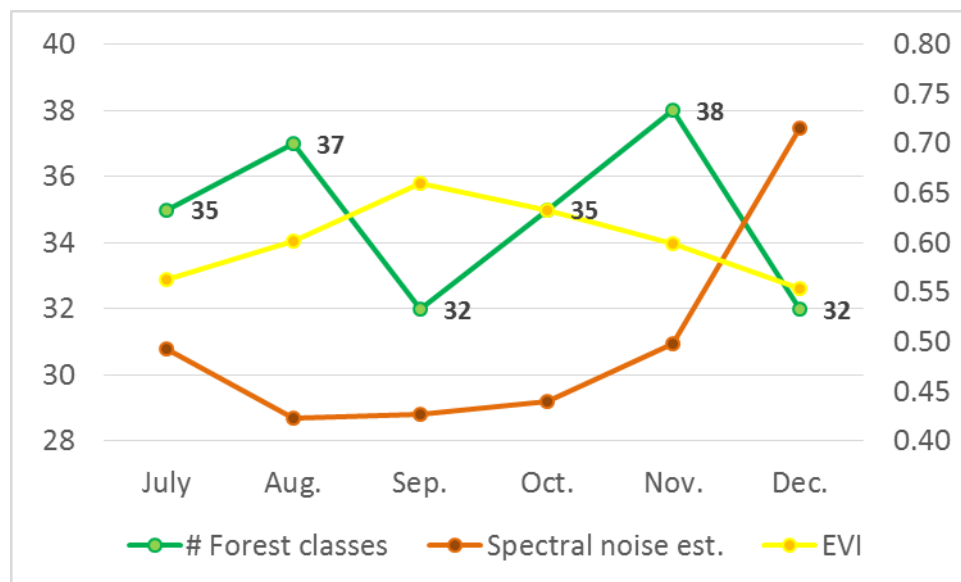


Figure 25. Number of spectrally distinct forest classes detected, estimate of spectral noise, EVI.

Where **Figure 24** focuses on the separability of the same forest types across the July to December time period, **Figure 25** illustrates the parallel approach, showing how many spectrally distinct forest classes can be detected in each monthly reflectance image. As a contrast to the number of spectrally distinct forest classes identified per month, EVI (as a measure of forest “greenness”) is presented, as well as the derived estimate of mean noise in the spectral reflectance data. Two things in particular should be noted: firstly, September coincides with the peak EVI (greenness), as well as the lowest number of spectrally distinct

forest types identified via the unsupervised classification. Lastly, while the unsupervised classification indicates that there are more spectrally distinct forest types present in the November imagery than any other month, the reflectance data is also estimated to be noisier in November (and in December).

Discussion

I. Impacts of bi-directional effects on canopy reflectance estimates

Much attention has been paid to the temporal effects of BRDF on spectral data (Morton et al. 2014; Lopes et al. 2016; J. Wu et al. 2016; Cherrington et al. 2016b; Cherrington et al. 2015b; Soudani and François 2014; Hilker et al. 2014; Bi et al. 2015; Xu et al. 2015), but not so much attention has been paid to its effects on the spatial variation of spectral data (Toivonen et al. 2006; Hansen et al. 2008; Potapov et al. 2012; Nagol et al. 2015; Muro et al. 2016). Where artefact-free reflectance data are seen as indispensable for studies relating to forest cover, corrections of Landsat data have largely focused on radiometric calibration, and removal of atmospheric and topographic artefacts in such imagery (Cuoet et al 2010; Hansen and Loveland 2012; Ediriweera et al. 2013; Nagol et al. 2015). Further, because the FOV of the sensors on the different Landsat satellites are small (15°), conventional wisdom - as expressed in different studies (Toivonen et al. 2006; Hansen et al. 2008; Hansen and Loveland 2012) - has generally been that corrections for bi-directional effects are not necessary because it has been assumed that the variation in reflectance due to such angular effects has been minimal.

This study's findings, however, indicate that there are indeed artefacts caused by the variation in viewing angle of the sensors on the Landsat satellites. That variation is evident both when one examines the raw Landsat surface reflectance data, and when one compares that data with reference datasets such as MODIS which have been corrected for angular effects (i.e. BRDF). And what is even more remarkable is that the BRDF-corrected MODIS data itself lacks the across-track anisotropy in its reflectance which is apparent in the Landsat surface reflectance data. This would seem to indicate an effective BRDF correction of the MODIS data.

It is likewise useful to examine what the findings of this study indicate in terms of the magnitude of BRDF effects per spectral band, and the overall trend in terms of how BRDF affects forest spectral reflectance. For instance, **Table 2** indicates that when comparing data from two different orbits (Landsat paths 227 and 228), in both cases, all spectral bands are affected to some degree by BRDF, although the effects appear greatest in the near-infrared band of the Landsat sensors. And where the near-infrared spectral channels are used in a range of applications – from deriving vegetation indices to use in mapping forests – the implication would be that BRDF may have a significant impact on endeavours such as forest mapping. In the case of the Landsat-5 Thematic Mapper data (path 228), across the sensor scan track, reflectance was estimated to vary by 3.29%, while in the Landsat-7 Enhanced Thematic Mapper+ data (path 227), reflectance was estimated to vary by 4.18%. And in both cases, it was the red spectral channel which indicated the lowest variation in reflectance across track. It is likewise assumed that the differences in such reflectance gradients between the two may be due to differences between the two Landsat sensors, as well as differences in reflectances of the forests themselves, as the data come from distinct regions of French Guiana. It may also

be that the impact of BRDF differs by date, with the Landsat-5 data acquired in early September, while the Landsat-7 data was acquired in late September. It would likewise be useful to assess the degree to which such BRDF effects differ by date, as well as by latitude.

Further, with the overall Landsat FOV being 15° , these variations in reflectance across track translate to increases in reflectance of between 0.09% and 0.28% for each degree increase in the scan angle for the Landsat-7 data, and an increase of between 0.06% and 0.22% for each degree increase in the scan angle for the Landsat-5 data. While the magnitude of the reflectance variation differed by spectral band and by satellite sensor, the overall trend is similar. That is, aside from local variations, in general, the Landsat reflectance estimates were higher on the 'sunlit' western portions of each image, and lower on the eastern portions of the image, which the sensors would be viewing in shadow. That finding was likewise similar to what was observed in terms of the bias between reflectance estimates from Landsat and MODIS, with the BRDF-corrected MODIS reference reflectance data indicating that the forests on the eastern edges of the Landsat image swaths should have higher reflectances than estimated with Landsat, with the opposite trend for forests on the western edges of Landsat swaths. Thus, corrections of BRDF effects in the Landsat reflectance imagery would involve increasing the reflectance of the eastern areas, and lowering the reflectance of western areas.

In terms of artefacts in Landsat reflectance data which must be addressed to allow such data to be used for studies related to the mapping of forests, corrections must be made for BRDF, as radiometric calibration, and topographic and atmospheric corrections are not sufficient. Further along that line of thought, a necessary line of future research would be the assessment of how angular effects in Landsat reflectance (i.e. BRDF) ultimately also affect the spectral classification of forest types.

II. Impacts of bi-directional effects on the mapping of the spatial distribution of forest types

In terms of the results depicted in Figures 3-4, this study has helped address a source of doubt with regard to the science of remote sensing. What has been demonstrated is that small differences in sensor acquisition parameters can result in forests' spectral reflectance being distorted so much that the same area imaged will yield extremely different estimates of forest type distribution. It is also very illustrative that two mosaics assembled from the same input Landsat datasets, but with one different treatment (i.e. BRDF correction) would result in maps which are over 70% different. The magnitude may speak more to the extent to which the Landsat reflectance estimates were modified during the BRDF correction process, but it nonetheless brings home the point that changes in the input reflectance data can greatly distort potential estimates of forest type distribution.

This study also yielded insights in terms of how different sensors may be used to estimate forest type distributions, by way of the comparisons of the results generated from Landsat versus those generated using the MODIS data. In this case, the largest segment of the Landsat mosaic used pertained to the same acquisition date as the MODIS Terra and MODIS Aqua images used, and yet, spatial resolution notwithstanding, the maps derived from the images were very different. In the case of the three images not corrected for angular distortions in reflectance, forest type distributions appeared to mirror and be distorted by the sensor scanning tracks. Thus, the maps produced resulted in distributions which appeared extremely

unrealistic (e.g. forests which only extend to the boundaries of the seams between two images). Since the MODIS imagery was also acquired within four hours of each other, it could also be appreciated how much reflectance changes diurnally. For instance, in the east of French Guiana, in the morning image, some areas were classified as having the reflectance of open forest, but four hours later, the same areas were identified as swamp forest. And while the difference in pixel size between Landsat and MODIS (30m versus 463m) may partly explain why the Landsat and MODIS results differed, they do not explain why both sets of MODIS results differed, which can thus only be posited to the differences in acquisition parameters.

While validation of the mapping has not yet been conducted, the study served its purpose in indicating that spectral classifications of forest type will change based on treatments to the input imagery. However, it would appear that much more attention is being focused on merely mapping forests (versus non-forest areas) than on use of spectral methods for identifying and discriminating between different forest types. Nonetheless, over the past decade or so, a number of key studies have emerged which have highlighted the need for BRDF corrections of Landsat imagery (Toivonen et al. 2006; Hansen et al. 2008; Potapov et al. 2012; Muro et al. 2016). Where standard texts highlight the need for correcting remote sensing for atmospheric and topographic effects (Lillesand et al. 2007; Jensen 2006; GOC-GOLD 2012), BRDF corrections, particularly for Landsat, are not yet treated as standard.

Although the exercise of determining spectral separability based on the application of and the lack of BRDF corrections may not count as validation of this study per se, it does serve to show how structurally distinct forests may not appear so distinct in imagery affected by sun-sensor geometry-related artefacts. So, for example, in the uncorrected imagery, open canopy and dissected canopy forests may have been difficult to discriminate, even as they were shown to be highly separable in BRDF-corrected imagery. The overall increase in separability of different forest types would thus seem to validate the efficacy of using BRDF-corrected data. It is likewise assumed that such effects would not, therefore, be limited to French Guiana, but that in terms of methodological improvements in forest type mapping, likely such techniques as pioneered in this study could be helpful in forest type discrimination in other tropical territories.

It should also be noted that while this study follows earlier works (e.g. (Girou 2001; Gond et al. 2011; Guitet et al. 2015)) in generating a new iteration of forest type mapping of French Guiana, it was not the objective per se of this study to produce a map of forest types. Rather, this study explored how the observation of spectral reflectance properties – which represent the response of vegetation to radiation – are affected by bi-directional effects. This study has merely scratched the surface of an important issue within remote sensing, and likely there is a great deal of research that needs to be done as follow-up. One such effort would be the use of field data and radiative transfer modelling (per studies like Gastellu-Etchegorry et al. 2003; J. Gastellu-Etchegorry et al. 2012; Gastellu-Etchegorry et al. 2015) to understand the mechanisms by which different forest structures – such as the ones mapped here – contribute to distinct patterns of spectral response. For instance, what is it exactly that makes a forest with a regular canopy reflect light differently from one with an irregular or an open canopy? Also, beyond structural differences, there are biological and bio-chemical distinctions at play as well, raising more questions. For instance, are the differences between the two

aforementioned forest types just constrained to structural differences, or do they reflect differently in French Guiana because such forests also possess different floristic compositions? Are they due to other ecological considerations (as per studies like Pélissier et al. 2002; Pelissier and Riéra 1993; Pélissier et al. 1998)? Such questions also provide for a range of avenues of future research.

III. Seasonal variation of estimates of forest type distribution

This study tested the simple hypothesis that evergreen forests should demonstrate a certain spectral stability during the course of a season. This was shown not to be the case (using 2 approaches), and is likely due to phenological changes within evergreen forests. In terms of the first method, the Jeffries-Matusita distance measures would seem to indicate that the spectral profiles of the same areas of forest (i.e. the training areas used) change sufficiently during the course of 6 months, noise notwithstanding. In terms of the second method, the number of spectrally distinct forest types changes from month to month, independent of the first approach. While the high number of spectrally distinct forest types observed in November is likely the product of the noise, for the periods of August to October, the spectral noise appears lower, the data thus more comparable, yet the number of spectrally distinct forest types is higher in August than in September or October. One explanation, indicated by the EVI data, is that leaf flushing in September may mask spectral distinctions between forest types. Overall in terms of the numbers of spectrally distinguishable forest types, and how those numbers change over time, it is obvious that on the ground, new forest types are not suddenly appearing only during certain months and disappearing in others. Rather, the spectral boundaries between real forest types – likely due to changes in forest condition – are being blurred month-to-month. Further research needs to be done to link factors like phenology, temperature, rainfall, and radiation to the changing spectral profiles of the area's forests.

While this analysis indicates that higher spectral bandwidth (i.e. the use of more spectral channels) is linked to better discrimination of forest types, this analysis also indicates that the SWIR bands are crucial to forest discrimination, more so than the VNIR bands. This is shown to be the case, independent of month. The VNIR data was less effective at discriminating forest types than the band combinations which included SWIR bands. In fact, the 4-band combination using the 2 SWIR bands showed a higher separability of forest types than the combination using only 1 SWIR band. This is interesting to note in light of the fact that commercial satellite sensors have generally stuck to the 'menu' of VNIR bands, with the exception of the recently-launched WorldView-3 satellite, which possesses SWIR bands (Lillesand et al. 2007). The importance of the SWIR bands is likely due to their ability to discriminate the subtle differences in the moisture content of vegetation types – likely what is being observed with the different forest types in French Guiana (USGS 2013). In contrast with the SWIR data, differences between vegetation types are lower in the VNIR range (Lillesand et al. 2007).

In terms of implications for other tropical forest territories, this study has essentially served as a case study for how readily accessible remote sensing data can be put to use for both inventorying and monitoring forest. As reflectance data is a principal input to forest cover classification, this study has demonstrated how monthly mean reflectance estimates can be

derived from the existing time-series of data, such as MODIS' 15 year archive. Where previous remote sensing studies generally focused on classifying reflectance data from a single date, in the course of this analysis, monthly mean reflectance estimates were assembled for French Guiana and the broader Guiana Shield. However, even having assembled 15 years of observations, it was still impossible to image the Guiana Shield cloud-free during the height of the rainy season – likely to be the case in other regions. The clearest imagery was confined to 6 months (July-December), and even so, it was estimated that only 3 months of data had low 'noise.' Lastly, it is acknowledged that the technique used in assembling monthly reflectance estimates is probably more applicable to French Guiana than other areas due to the territory's low rate of deforestation. In other regions, where forests would not be as 'stable,' averaging data for 15 years would likely result in pixel signals from forest and deforested areas being mixed together.

III. Synthesis

Taking the aforementioned results into context, two main conclusions are arrived at: (i) that spectral reflectance data of forest canopies are indeed affected by bi-directional effects, but (ii) those effects can be corrected for, and when they are, they lead to improved ways to assess forests' spatial and temporal variation.

Further, even though French Guiana's forests are evergreen (i.e. most of the trees do not shed their leaves in the dry season), the satellite data does appear to pick up on temporal variations which may aid in discriminating between forest types. For instance, the BRDF-corrected MODIS data for August shows the vegetation at the greatest degree of spectral separability compared to other months. However, these studies likewise point to methodological limitations of using spectral reflectance data to examine the spatial heterogeneity of tropical forests. One such limitation takes the form of the spatial resolution (i.e. level of spatial detail) of the imagery used. It is known that Amazonian forests – and French Guiana forests by extension – are extremely diverse, with hundreds of species per hectare. If, following some key assumptions of remote sensing of forests, that individual species possess their own respective spectral response patterns (i.e. spectral signatures), then it would follow that at the scale used in the previous studies (pixels which represent roughly 1/10th of a hectare), then each pixel in French Guiana must be a conglomeration of many spectral signatures (Jensen 2006; Lillesand et al. 2007).

Other studies (Barbier et al. 2012; Coutron et al. 2012) have proposed studying forest types at the scale of individual crowns rather than mixtures of the spectral responses of several crowns. This would be done using very high spatial resolution (VHSR) remotely sensed data. It goes without saying, however, that in terms of the state of the art, it is currently quite challenging to conduct such an assessment at the scale of all of French Guiana, on the grounds that a complete coverage of such VHSR data does not yet exist for French Guiana. Persistent cloud cover over French Guiana also makes obtaining such data difficult. Furthermore, from a methodological and scientific perspective, even if a "wall-to-wall" mosaic of VHSR imagery of French Guiana did exist, this study's findings suggest that it would definitely need to be corrected for BRDF, not a trivial matter. Additionally, with the exception of the commercial WorldView-3 satellite, the majority of satellites which collect VHSR data do not acquire spectral reflectance data in the short-wave infrared (SWIR) portions of the electromagnetic

spectrum, even as studies (including the 3rd section of this Chapter) suggest that the SWIR bands are essential for the discrimination of forest types (Ferreira et al. 2015; Clark and Roberts 2012; Feret et al. 2013; Zhang et al. 2006). In other words, even if there existed a mosaic of VHSR imagery covering all of French Guiana and corrected for BRDF, it is very likely that based on the usual 'formula' of such satellites having spectral bands only in the visible and near-infrared ranges, this would still be insufficient for discriminating forest types.

Those can be considered as implications of this Chapter regarding remote sensing techniques. Ultimately, however, what are the implications of these findings in terms of tropical forest ecology? Mainly, these studies related to spatial variation suggest that forests with different canopy structures and different floristic compositions can be differentiated, to some degree, by remote sensing. These thus suggest, in line with earlier studies (Gond et al. 2011; Guitet et al. 2015) that French Guiana is no "green carpet," and that is promising. In other words, these findings partly suggest that it is indeed possible to use remote sensing to map tropical forests based on distinctions in structure and floristic composition. The extent to which that was actually done for French Guiana is, unfortunately, unknown due to the lack of field validation of the remote sensing analyses carried out.

Further, it is also known that there are limitations outright to the approach used, and these are particularly highlighted by the final section of this Chapter. One underlying assumption of the second study – which is reflected in countless other forest remote sensing studies – is that forest types can be identified (i) based primarily on spectral reflectance estimates which are (ii) observed at a single snapshot in time. Other studies, however, have hinted that the main limitation of such approaches is that these do not consider how forests, particularly tropical ones change in time, and propose understanding forest types through more holistic analyses which incorporate (i) how forests change over time, and (ii) traits in addition to spectral reflectance (Ustin and Gamon 2010; Huesca et al. 2015). Those studies also share the perspective that VHSR imagery at the scale of the crown-level and sub crown-level would also be necessary for effective discrimination of forest types, building on the arguments presented in earlier studies (Barbier et al. 2012; Couteron et al. 2012). However, on the subject of using temporal information to distinguish between forest types, the following chapter will shed some light on that topic.

On the broader topic of the spatial variation of tropical forests, as indicated, there were methodological limitations of this Chapter's sections (e.g. the scale which was possible, the lack of field verification). There remains an underlying question as to whether the spatial heterogeneity represented in spectral reflectance data necessarily represent actual patterns of spatial variation on the ground. The first section in this Chapter, focusing on how BRDF affects spectral reflectance data, certainly highlights this issue in showing that independent of potential sensor errors and anomalies, just due to the physics of observation by satellite sensor, the data captured possess sun-sensor geometry-related artefacts. Such effects compound other issues, such as distortions in reflectance caused by atmospheric haze and topographic shadowing, which altogether distort spectral reflectance data and make it difficult to properly represent forest spatial heterogeneity. Nonetheless, to the extent possible, this Chapter's sections utilized techniques to either correct for or minimize artefacts, such as the use of state of the art algorithms for the corrections. It is therefore expected that the spectral reflectance estimates derived were as error-free as possible, although the third chapter of this

thesis also examines how the aforementioned issues could be mitigated by the use of time-series decomposition techniques.

This Chapter's findings also inevitably lead to new research questions, which while not addressed in the following chapters do lay the foundation for future research:

- To what does the observed anisotropy in canopy spectral response in satellite sensors vary from month to month?
- To what extent is such anisotropy a function of geographic latitude?
- To what extent does such anisotropy depend on forest structure or on leaf biochemistry?

Chapter 2: Temporal variation of tropical forests

Overview of the chapter

In contrast to the previous chapter which focused on the spatial variation of tropical forests, this Chapter focuses on the temporal variation of those forests, specifically addressing the following research questions:

- i. To what extent does the observed seasonal variation in vegetation indices (VIs) of French Guiana correspond to seasonal climatic variation or to instrumental or atmospheric artefacts?
- ii. To what extent does VI variation modelled as a function only of solar elevation change correlate with remotely sensed observations?
- iii. Provided that the seasonal variation in VIs is not an artefact, what do corrected data indicate in terms of the seasonal patterns for tropical forests?

The first part of the chapter examines how bi-directional effects impact time-series of observations of forest vegetation, at a very broad scale and is based on a study published in the August 2016 special issue of the *IEEE Journal of Selected Topics in Remote Sensing*, IEEE JSTARS (Cherrington et al. 2016b). The second part of the chapter follows up by examining bi-directional effects on time-series, but at the plot level. In contrast, the third part of the chapter uses data corrected for bi-directional effects to examine what these indicate in terms of the phenological variation of specific types of forest. It is based on a study published in the December 2015 special issue of the *Revue Française de Photogrammétrie et de Télédétection*, RFPT (Cherrington et al. 2015b).

Introduction

Related to the issue of the spatial variation of tropical forests is their temporal variation, which can likewise be monitored and evaluated using remote sensing. Satellite-derived vegetation indices (VIs) have been touted as surrogates for monitoring phenological variation across vegetation types, with such data believed to be highly correlated to photosynthetic activity (Zhang et al. 2006; Balzarolo et al. 2016). One relevant area of study has been the greater Amazon rainforest, with various studies indicating that VIs can be used to monitor processes occurring in remote and otherwise inaccessible parts of the Amazon (Bi et al. 2015; Bradley et al. 2011; Huete et al. 2006; Saleska et al. 2007). However, other studies make the case that the variation in the VI data over the Amazon is merely due to changing solar and sensor viewing angles inducing the 'bi-directional reflectance distribution function' phenomena (Morton et al. 2014). That is, the observed reflectance of forests and the VIs derived therefrom will change when the solar and viewing angles change, even in the absence of actual change in the vegetation structure (Morton et al. 2014). Field studies in Australia and Brazil have likewise shown that reflectance and derived VI estimates can be spuriously increased merely due to increasing solar elevation (Galvão et al. 2004; Rahman et al. 2015).

Such research effectively called into question the feasibility of using VIs to study phenological variation (particularly in tropical forests), as such data are susceptible to BRDF impacts. One way in which BRDF impacts on variable angle sensors (e.g. the MODerate resolution Imaging Spectroradiometer, MODIS, and SPOT VEGETATION, VGT), are addressed is by normalizing reflectance data “to a standard sun-target-sensor geometry,” to allow for comparison of data originally acquired at distinct view angles (Liu 2003, Schaaf et al. 2011). While normalization techniques standardize viewing angle, the effect of solar elevation as a driver of BRDF remains (Rahman et al. 2015). Unresolved questions include: (i) how much the variation in solar elevation impacts VI estimates, and (ii) whether phenology can be detected in spite of BRDF.

I. Evaluating BRDF impacts on VI temporal variation at the regional scale

Simple hypotheses can be used to test the extent to which BRDF thus impacts VI data at a regional scale. One way is by analysing VI data from different regions on the same latitude. This is because while parts of the world on different latitudes experience different ranges of solar elevation variation, areas on the same latitude experience identical ranges. If trends observed in VI data are merely driven by BRDF, forests on the same latitude should display identical variation in VI data, all other things being equal. This Chapter thus seeks to determine whether or not forests near the equator (like those near the Amazon) do indeed display similar vegetation index trends, or whether whatever observed variation in VI data might be plausibly explained by environmental processes, such as seasonally-driven phenological variation. Another possibility is that observed variation is due to atmospheric contamination of the satellite data (Kaufman et al. 1992). Three hypotheses were thus proposed:

- (i) Temporal variation in VIs is merely an artefact driven by variation in solar elevation.
- (ii) Temporal variation in VIs is merely an artefact caused by atmospheric effects.
- (iii) Temporal variation in VIs is indicative of environmentally controlled phenological variation.

II. Evaluating BRDF impacts on VI temporal variation at the plot level

Conversely, where the majority of the earlier studies addressing on the issue of phenology in the greater Amazon have largely been focused on the regional level (thousands of square kilometres), it is also possible to investigate how remote sensing detects phenology at finer scales, such as that of 1-hectare forest plots. Further, one means of addressing the issue is by the use of radiative transfer modelling, a toolset previously used to suggest that phenological changes are not occurring (Morton et al. 2014). Radiative transfer models such as the Discrete Anisotropic Radiative Transfer (DART) model can be used to simulate changes in forest structure to answer questions about phenology (Gastellu-Etchegorry et al. 2003; Gastellu-Etchegorry et al. 2012; Gastellu-Etchegorry et al. 2015). This Chapter thus also seeks to build on earlier studies addressing whether tropical rainforest phenology is really being observed (Huete et al. 2006; Saleska et al. 2007) or is merely an instrumental artefact (Morton et al. 2014). This study thus sought to test the hypothesis that monthly variation in vegetation indices

observed by satellite sensors over the greater Amazon is not only driven by the monthly variation in solar elevation but is also symptomatic of phenological variation.

III. Assessing VI variation by forest type, using corrected data

Artefacts due to sun-sensor geometry are not insurmountable obstacles for data analysis, however, as BRDF-corrected data products do exist. NASA routinely generates surface reflectance products (e.g. MCD43B4) which are corrected for BRDF. These complement other available BRDF-corrected satellite-derived products such as the ‘fraction of green vegetation cover’ (FCOVER) product derived from the VEGETATION instrument (hereafter referred to as VGT), on SPOT-4 and SPOT-5 (Camacho et al. 2009, Baret et al. 2013). In addition, indices such as LAI, the Leaf Area Index, are “derived by explicitly accounting for changing viewing and illumination conditions” and are thus “free of sun-sensor geometry effects” such as BRDF (Bi et al. 2014). LAI products are available from MODIS, as well as from VGT.

Since BRDF affects reflectance estimates and consequently VIs, it might be that previously-reported trends – generated using uncorrected data – are invalid. However, as it is possible to utilize VIs which are either corrected for or unsusceptible to BRDF, such trends can and should be re-examined. Based on an earlier study utilizing VIs not corrected for BRDF (Pennec et al. 2011), French Guiana represents an appropriate case study for such re-examination. While the study focused primarily on the analysis of satellite data, it did show how seasonal patterns in both the Enhanced Vegetation Index (EVI) and the Shortwave Water Stress Index (SWSI) seemed to confirm the phenology indicated in an earlier botanical study (Sabatier & Puig 1986). (French Guiana’s seasons are generally divided between a ~long rainy season spanning December to July, and a shorter dry season spanning July-November - Sabatier 1985.) Nevertheless, since the satellite-based study of French Guiana used data not corrected for BRDF, questions remain as to whether the previously noted seasonality in the VIs is indeed valid. The principal objective of this part of the chapter was therefore to explore what BRDF-corrected VIs indicate regarding the seasonality (or possibly the lack thereof) of French Guiana’s forests, taking advantage of the ‘big data’ of over a decade of BRDF-corrected observations from both MODIS and VGT.

Results

I. Evaluating BRDF impacts on VI temporal variation at the regional scale

Characterization of VI variation

Table 9. Correlations among the enhanced vegetation index (EVI), the fraction of green vegetation cover index (FCOVER), and the leaf area index (LAI).

Comparison	Guiana Shield	central Africa	northern Borneo
EVI / FCOVER	0.69	0.91	0.32
EVI / LAI	0.66	0.71	0.40
FCOVER / LAI	0.74	0.89	0.83

Correlation analysis indicates that overall, there is a high degree of correlation between the indices (see **Table 9**). The exception is Borneo where although FCOVER and LAI values are highly correlated, EVI values are not highly correlated with the other VIs. That analysis is in accordance with **Figures 26-27**, which illustrate the average monthly variation in EVI, FCOVER, and LAI (as well as other variables) across the 3 regions. The figures also show that VI trends across the 3 regions differ substantially. For the Guiana Shield, the overall trend for the 3 VIs is a peak in September-October, although EVI also shows a smaller peak in April. For central Africa, the trend across the VIs is generally bi-modal, with peaks in March-April, and in September. For Borneo, the FCOVER and LAI trend is more or less flat, but bimodal in EVI.

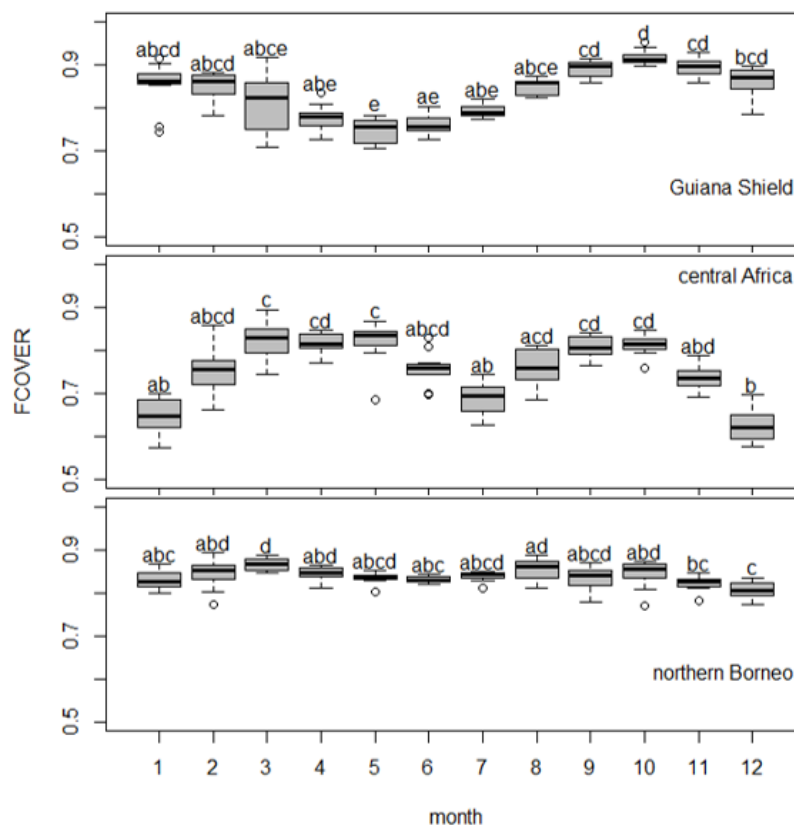


Figure 26. Monthly variation in FCOVER for each region.

The magnitudes of variation among the indices also differ region by region. For instance, for FCOVER values, in the Guiana Shield, monthly mean values generally range from 0.78 to 0.95, while for central Africa, those values range from 0.57 to 0.85, while for Borneo, the trend is much less dynamic, only ranging from 0.82 to 0.86. The non-parametric multi-comparison test (Kruskal Wallis) of the FCOVER data (shown in **Figure 26**) likewise indicates that for the Guiana Shield, in general, the peak in 'greenness' in October is significantly higher than in the wet season months of March to July (but not significantly higher than the wet season months of December to February). The analysis likewise indicates that for central Africa, FCOVER values in January, July, and December are significantly lower than in the wet season months. For Borneo, however, the analysis indicates low monthly variation in FCOVER, suggesting that 'greenness' is maintained year-round.

Correlation analysis also indicates that VI variations between regions are not strongly correlated, although the magnitude of the correlations varies by VI. FCOVER, for instance, possesses the overall weakest correlations, ranging from -0.34 between the Guiana Shield and central Africa to 0.02 between the Guiana Shield and Borneo, to 0.19 between central Africa and Borneo. The respective values are -0.04, -0.06, and 0.38 for LAI, and 0.52, 0.46, and 0.39 for EVI. This may suggest that MODIS-derived EVI is more susceptible to BRDF effects than the two VGT-derived VIs, although the correlations between the EVI values for the three regions are not particularly strong.

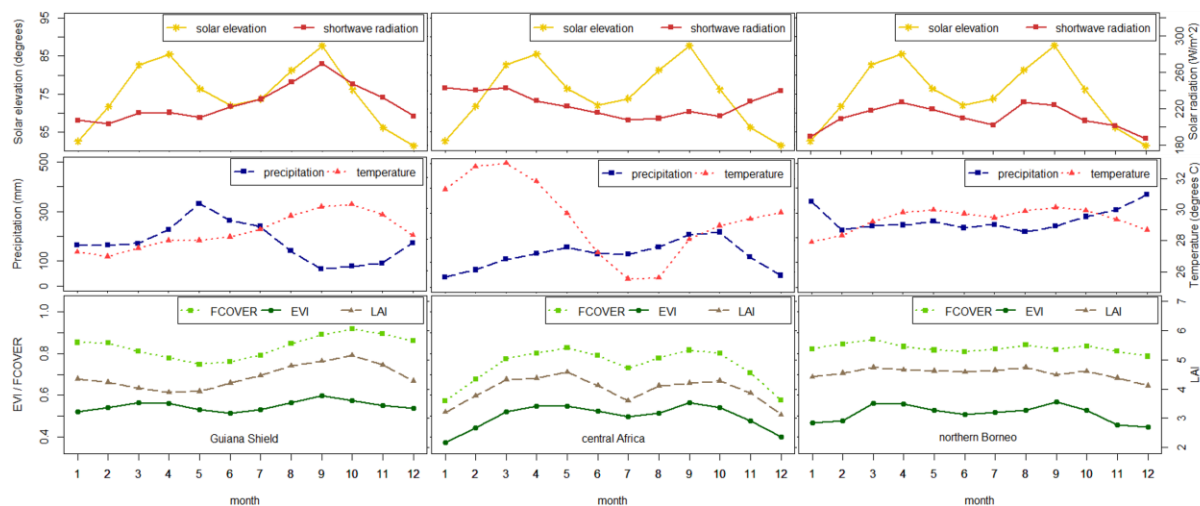


Figure 27. Average monthly variation (2002-2014) in solar elevation, incident shortwave solar radiation, precipitation, temperature, and the vegetation indices.

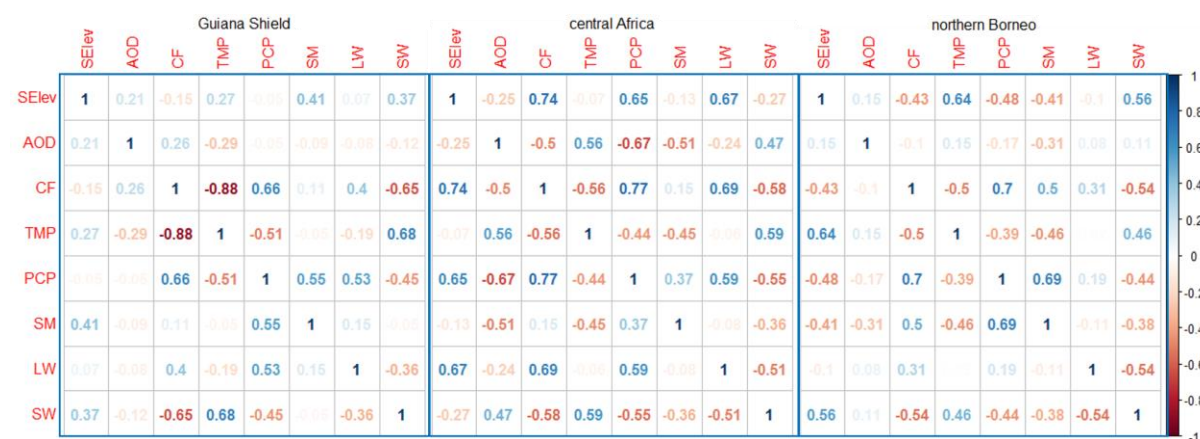


Figure 28. Correlations among the explanatory variables.

In terms of the differences between regions, as seen in **Figure 28**, a general trend is in terms of potential drivers of VI variation, explanatory variables co-vary differently in each region. For instance, while cloud fraction and temperature are negatively correlated in each of the 3 regions, in the Guianas, the correlation is strongly negative (-0.88), compared to more moderate negative correlations for central Africa (-0.56) and Borneo (-0.5). In contrast, there is a strong correlation between temperature and shortwave solar radiation in the Guiana Shield (0.68), but a more moderate correlation for central Africa (0.59), and a moderate negative

correlation for Borneo (-0.54). In general, strong correlations between variables in the Guiana Shield were fewer, compared to central Africa and Borneo. Additionally, solar elevation is only weakly correlated with other variables in the Guianas, but the covariations are stronger in central Africa and Borneo.

Table 10 presents the results of the 27 multiple linear regressions models, while **Table 11** illustrates the results of different subsets of those models. For both the Guiana Shield and central Africa, as indicated by both the R^2 and the AIC, the models with the best fit were the ones modelling VI variation as a function of environmental factors (ENV). For instance, for the Guiana Shield, the environmental model greatly outperformed either of the other two models (e.g. AIC of -539 vs. -405 and -419). For EVI for both the Guiana Shield and central Africa, the environmental model's fit was strong ($R^2 > 0.7$), while for Borneo, there was poor fit across models ($R^2 < 0.25$).

Table 10. Summary of main regression models analysed (EVI= enhanced vegetation index, FCOVER = fraction of green vegetation cover index, LAI = leaf area index, BRDF = BRDF model, ATM = atmospheric model, ENV = environmental model).

Zone	VI	Model	R^2	RSE	AIC
Guiana Shield	EVI	BRDF	0.32	0.025	-269
		ATM	0.52	0.021	-288
		ENV	0.72	0.017	-314
	FCOVER	BRDF	0.03	0.055	-405
		ATM	0.14	0.052	-419
		ENV	0.65	0.033	-539
	LAI	BRDF	0.00	0.448	174
		ATM	0.39	0.353	109
		ENV	0.56	0.301	68
central Africa	EVI	BRDF	0.66	0.037	-521
		ATM	0.63	0.038	-508
		ENV	0.73	0.033	-546
	FCOVER	BRDF	0.61	0.056	-395
		ATM	0.63	0.056	-402
		ENV	0.73	0.049	-436
	LAI	BRDF	0.38	0.461	183
		ATM	0.31	0.485	198
		ENV	0.48	0.426	165
northern Borneo	EVI	BRDF	0.17	0.085	-284
		ATM	0.16	0.086	-281
		ENV	0.15	0.087	-274
	FCOVER	BRDF	0.14	0.028	-593
		ATM	0.09	0.029	-583
		ENV	0.13	0.029	-583
	LAI	BRDF	0.25	0.216	-28
		ATM	0.18	0.226	-14
		ENV	0.23	0.221	-17

Overall, the model fit for the regression of VIs as a function of solar elevation (BRDF) was weaker than other models, although varying by region and by VI. For instance, for both EVI and FCOVER for central Africa, the R² of the BRDF model exceeded 0.6, indicating that solar elevation variation strongly explained variation in those two VIs. The atmospheric effects models (ATM) did not outperform the environmental models, but in various cases, model fit was nonetheless strong, exceeding 0.6 for EVI and FCOVER for central Africa, and exceeding 0.5 for EVI for the Guiana Shield. However, as with the BRDF models, the atmospheric effects models did not outperform the environmental models for French Guiana or central Africa.

While the environmental models for French Guiana and central Africa generally possessed much explanatory power, as illustrated in Table 4, much of the explanatory power of the environmental models was provided by a sole variable, precipitation. For instance, for French Guiana, the environmental model for EVI possessed an R² of 0.72, but when precipitation was excluded, the R² fell to 0.58. In contrast, the R² of a precipitation-only model was 0.59, very close to the model based on temperature, solar radiation, and soil moisture together. The differences in AIC values, however, were higher, with the former (-304) outperforming the latter (-292) to a greater degree. Similarly, in central Africa, the environmental model for EVI had an R² of 0.73, which likewise fell to 0.57 when precipitation was excluded. In contrast, the R² of the precipitation-only model was 0.62. Even for Borneo, with its overall weak model fits, precipitation provided a large portion of the explanatory power relative to other variables (e.g. 0.09 for precipitation only vs. 0.15 for the full environmental model). However, AIC values for Borneo for the precipitation-only model and the full environmental model were similar (-272 vs. -274).

Table 11. Supplementary regression models analysed (EVI = enhanced vegetation index, LW = longwave radiation, PCP = precipitation, SM = soil moisture, SW = shortwave radiation, TMP = temperature).

Zone	Model (EVI as fxn. of)	R ²	RSE	AIC
Guiana Shield	TMP, SW, LW, SM	0.58	0.020	-292
	PCP, TMP	0.66	0.018	-314
	PCP	0.59	0.018	-304
	TMP	0.54	0.021	-297
central Africa	TMP, SW, LW, SM	0.57	0.042	-483
	PCP, TMP	0.63	0.038	-508
	PCP	0.62	0.039	-507
	TMP	0.07	0.061	-381
northern Borneo	TMP, SW, LW, SM	0.13	0.088	-272
	PCP, TMP	0.14	0.087	-277
	PCP	0.09	0.089	-272
	TMP	0.10	0.089	-273

In contrast to the relatively high explanatory power of precipitation-only models for the Guiana Shield and central Africa, for the former, temperature also had high explanatory power (R² of 0.54, vs. 0.59 for precipitation). Likewise, for that region, temperature and

precipitation provided most of the explanatory power (R^2 of 0.66, vs. 0.72 for the full model). The R^2 of the combined temperature-precipitation model suggests potential interactions between explanatory variables (see the correlations in **Figure 28**). The complete models shown in **Table 12** generally indicate that – at least for the Guianas and central Africa – most of the VI variation (69-84% in the case of EVI and FCOVER) can be explained as a function of the combined effects of BRDF, atmospheric effects, and environmental variation. However, these models still do not explain even half of the VI variation of Borneo.

Table 12. Regression models analysed using all variables, contrasted with the enhanced vegetation index (EVI), the fraction of green vegetation cover index (FCOVER), and the leaf area index (LAI).

Zone	VI	R^2	RSE	AIC
Guiana Shield	EVI	0.81	0.014	-331
	FCOVER	0.69	0.032	-547
	LAI	0.60	0.290	60
central Africa	EVI	0.84	0.026	-608
	FCOVER	0.82	0.040	-488
	LAI	0.60	0.379	135
northern Borneo	EVI	0.23	0.084	-281
	FCOVER	0.36	0.025	-620
	LAI	0.37	0.202	-40

II. Evaluating BRDF impacts on VI temporal variation at the plot level

Characterization of daily variation in EVI

Modelling of EVI variation across individual days indicates that such variation is proportional to the diurnal variation in solar elevation (**Figure 29**). As such, the variation in EVI on 15 September (an increase of 14.8% across the day) is higher than that of 15 December (an increase of only 9%), and the overall mean EVI of the former is higher than that of the latter (**Table 13**).

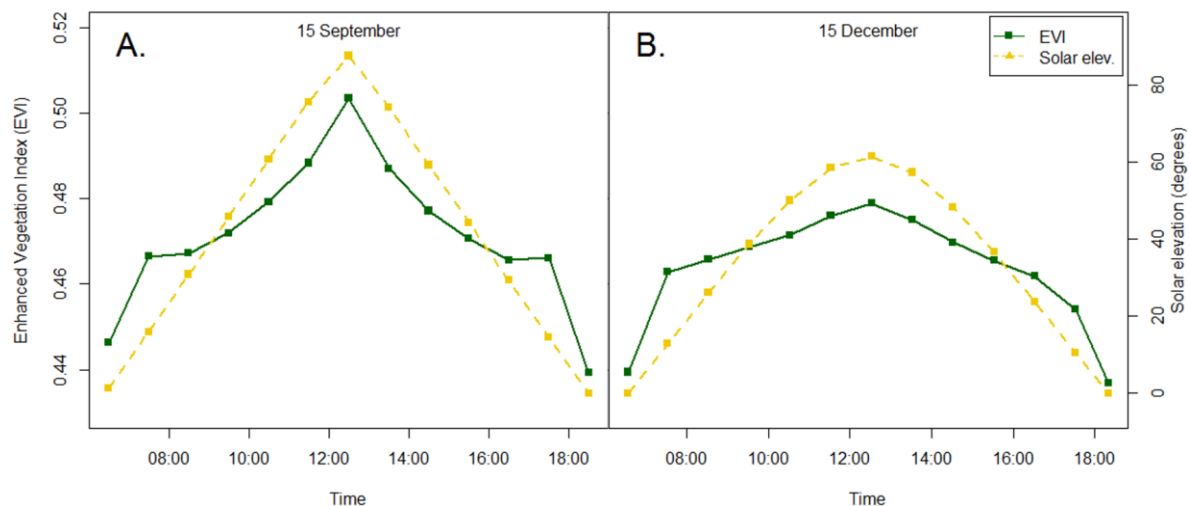


Figure 29. Daily variation in EVI from radiative transfer modelling at Paracou for 15 September (left) and 15 December (right).

Table 13. DART-derived reflectance values and EVI for the Paracou plot, on 15 September and 15 December.

Parameter	Reflectance			EVI	Date
	Blue	Red	NIR		
Mean	0.91%	0.92%	24.07%	0.4714	15 September
Minimum	0.78%	0.78%	22.26%	0.4393	
Maximum	1.15%	1.17%	26.27%	0.5034	
(Max-Min)/Min (%)	32.30%	33.03%	24.40%	47.64%	
Mean	0.86%	0.87%	23.55%	0.4636	15 December
Minimum	0.77%	0.77%	22.12%	0.4370	
Maximum	1.03%	1.04%	24.55%	0.4789	
(Max-Min)/Min (%)	25.79%	25.82%	24.20%	47.35%	

Where the previous analyses assumed a spherical LAD distribution for the vegetation, assuming alternative LADs likewise translates to great variation in terms of EVI estimates. For instance, the average EVI assuming a planophile distribution was 12.8% higher than the EVI modelled assuming an erectophile LAD. EVI modelled assuming a planophile LAD was likewise 9% higher, on average, than EVI estimated assuming a spherical distribution, but only 3.5% higher than EVI assuming a plagiophile LAD (**Figure 30A**). In addition, when PAI values were modified to 50% and 75% of their original observed values (but assuming a spherical LAD), EVI estimates were likewise altered (**Figure 30B**). At 12:30pm, the maximum modelled EVI (0.5034) corresponded to the estimate derived from the plot with the maximum (100%) PAI, while the plot with 75% PAI possessed an estimated EVI of 0.4958, and the plot with 50% PAI possessed an estimated EVI of 0.4597. As when varying LAD, EVI estimates with varying PAI can be seen to follow the same trend as solar elevation, peaking when solar elevation peaks. Depicting EVI variation as a function of both varying LAD and PAI (**Figure 30C**) depicts similar trends: for each of the 4 LADs, at 12:30pm on 15 September, EVI is highest under the planophile distribution, but also highest when PAI is highest.

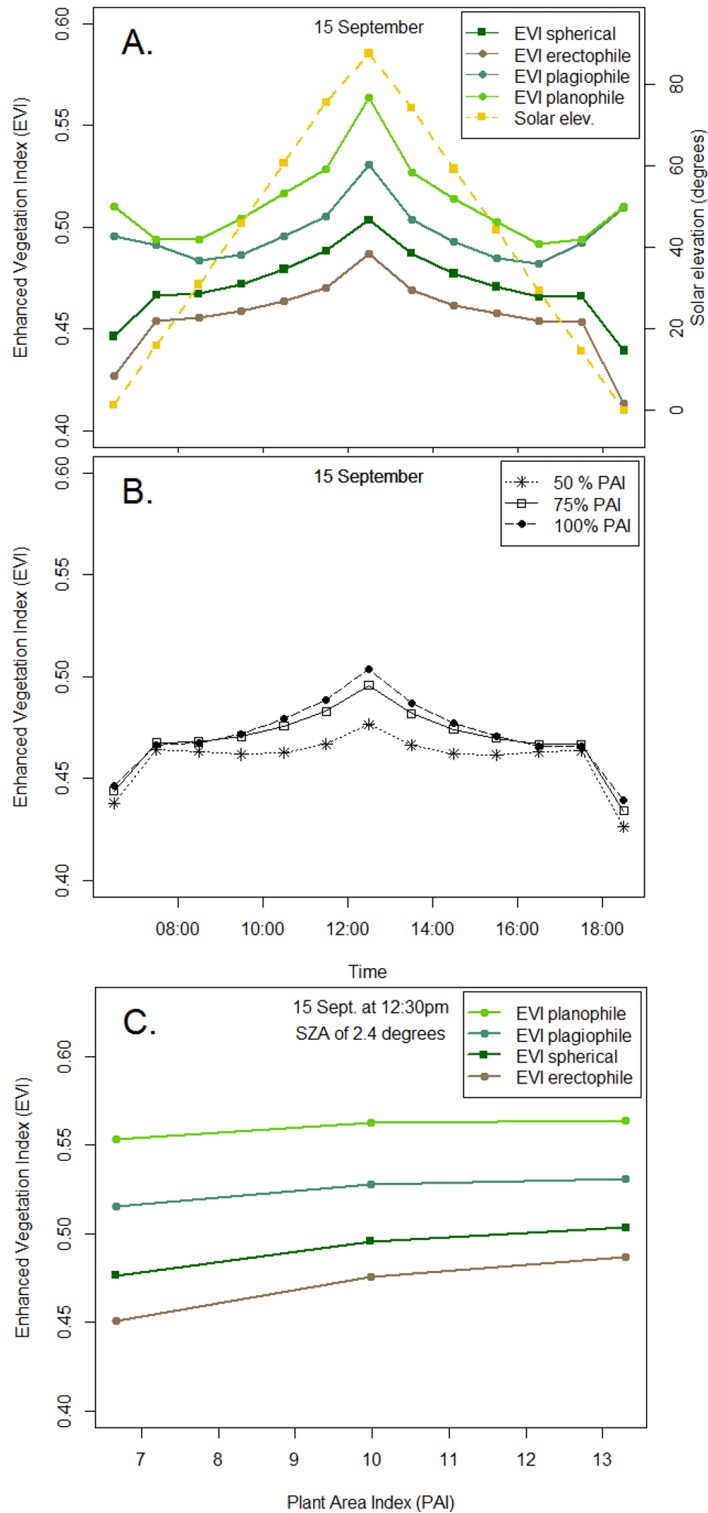


Figure 30. Modelled daily variation in EVI at Paracou for 15 September, under varying: A) Leaf Angle Distributions (LAD); B) Plant Area Index (50%, 75%, and 100% of the PAI estimated in September 2013); C) PAI and LAD.

Characterization of monthly variation in EVI at solar noon

Figure 31 illustrates that the monthly variation in EVI follows the monthly changes in solar elevation at solar noon. For instance, solar elevation peaks in both April and September,

likewise leading to peaks in modelled EVI for those periods. It can also be observed that the trends between Itoupé, Nouragues, and Paracou are highly correlated (Pearson’s r values for each is 0.99), although they differ in magnitude. In terms of understanding those differences in magnitude, **Table 14** likewise shows that the EVI differences were related to different mean NIR reflectance values, with Paracou having the highest modelled NIR reflectance.

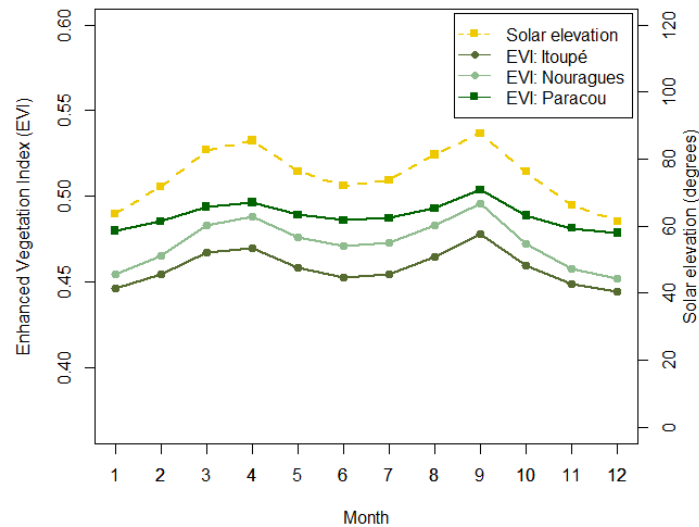


Figure 31. Monthly variation in solar elevation at solar noon and modelled variation in EVI at the three study sites (based on a spherical LAD).

Table 14. DART-derived reflectance and EVI for the three study plots.

Parameter	Reflectance			EVI	Plot
	Blue	Red	NIR		
Mean	1.00%	1.01%	23.35%	0.4580	Itoupé
Minimum	0.89%	0.90%	23.39%	0.4587	
Maximum	1.14%	1.17%	23.45%	0.4596	
(Max-Min)/Min (%)	22.02%	22.70%	23.53%	46.10%	
Mean	0.98%	1.00%	24.23%	0.4726	Nouragues
Minimum	0.85%	0.86%	24.37%	0.4747	
Maximum	1.14%	1.17%	24.47%	0.4764	
(Max-Min)/Min (%)	25.36%	26.38%	24.53%	47.73%	
Mean	1.03%	1.04%	25.22%	0.4885	Paracou
Minimum	0.94%	0.95%	25.21%	0.4883	
Maximum	1.16%	1.18%	25.19%	0.4879	
(Max-Min)/Min (%)	18.29%	19.00%	25.14%	48.72%	

Comparison of modelled and observed EVI

Whereas the previous sections focused on the assumption that vegetation density at the study plots does not change over time, **Figure 32A** compares the data modelled based on that assumption with observed data from MODIS. It indicates that the modelled pattern based on such an assumption does not correlate highly with the satellite data (Pearson’s $r = 0.46$; see **Figure 33**). However, as shown in **Figure 32B**, when canopy reflectance is modelled based on

the assumption that vegetation density is changing (i.e. phenology), the variation of the model-derived EVI estimates more closely correlate with the variation of the MODIS-derived EVI (Pearson's $r = 0.70$).

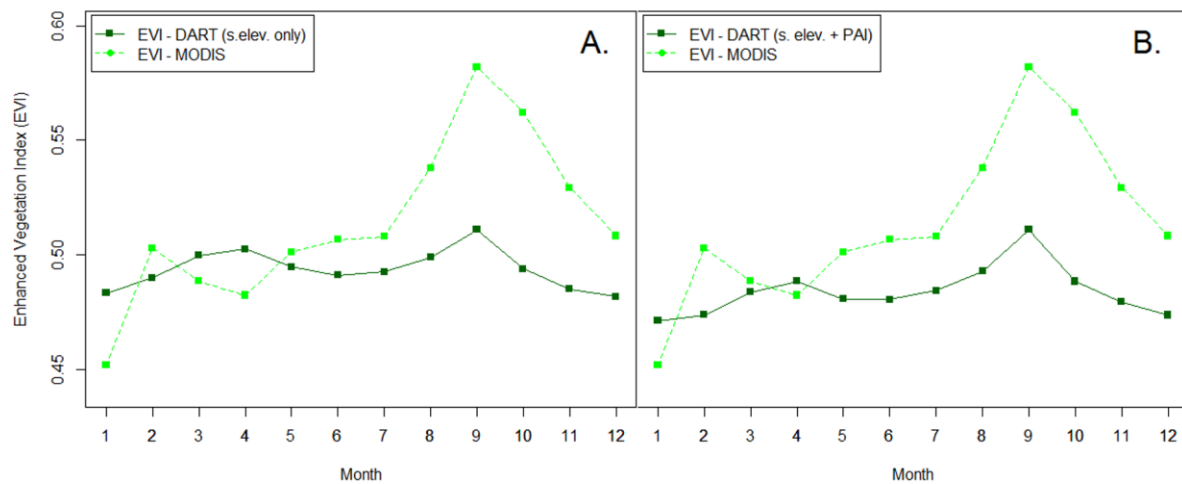


Figure 32. Compared monthly variation in EVI observed at Paracou, (MODIS) and DART-modelled: A: based on a spherical LAD (Leaf Angle Distribution) with solar elevation variation only; B: based on both solar elevation variation and monthly variation in PAI (Plant Area Index).

While the DART-derived EVI estimates had their PAI variation patterned off of the variation in MODIS LAI, these estimates nonetheless also possess a stronger correlation with the MODIS-derived EVI (0.70) than they do with just the variation in LAI (0.53), although they do also possess a strong correlation with the pattern of solar elevation variation (0.84). Likewise, even though DART was not parameterized based on the monthly variation in aerosol optical depth (AOD), since the correlation between AOD and observed EVI is lower in magnitude than the correlation between LAI and observed EVI (-0.66 versus 0.86), it is also suspected that modelling EVI as a function of solar elevation and AOD variation would not have yielded a strong correlation between the modelled EVI and the observed EVI.

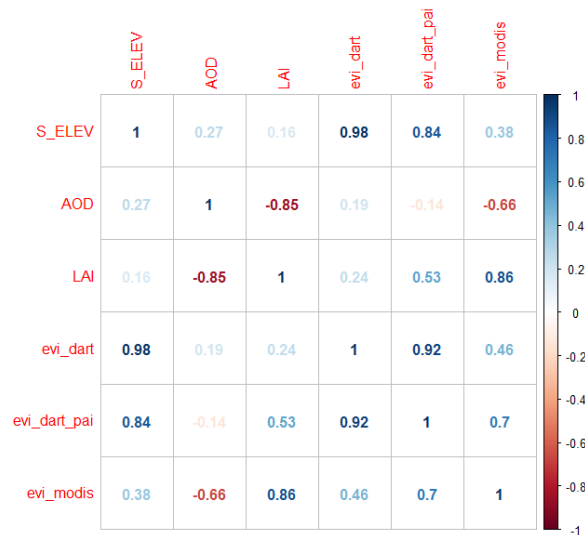


Figure 33. Correlations among observed EVI (evi_modis), solar variation-modelled EVI (evi_dart), solar variation and PAI variation-modelled EVI (evi_dart_pai), solar elevation (S_ELEV), aerosol optical depth (AOD), and leaf area index (LAI), for the Paracou plot.

III. Assessing VI variation by forest type, using corrected data

VI variation at the level of all of French Guiana

In contrast with the previous sections which were examining BRDF impacts, this section examines what VI data already corrected for BRDF impacts indicate with regard to temporal variation. Comparison of the mean monthly values for the different VIs – derived from ~12 years of data – show what appear to be distinct seasonal patterns (**Figure 34**). In general, the patterns appear more distinct for the 4 BRDF-corrected VIs shown, as compared to the single uncorrected VI shown, with the latter being essentially a reproduction from the data presented in an earlier study (Pennec et al. 2011). The 2 MODIS-derived products (EVI and LAI) indicate that the peak of ‘greenness’ / vegetation vigor is in September. By comparison, the VGT-derived products (FCOVER and LAI) and the EVI estimate not corrected for BRDF, all indicate a peak in October. It is noted, however, that there are differences in magnitude between the MODIS- and VGT-derived LAI estimates. The MODIS-derived LAI mean ranges from 4.39 to 5.99, while the VGT-derived LAI has a lower range, from 3.67 to 5. Nevertheless, correlation analysis indicated that the two LAI datasets were highly correlated, with a correlation coefficient of 0.83.

The effect of the BRDF correction can also be noted by comparing the monthly variation between the BRDF-uncorrected and the BRDF-corrected EVI data. For instance, the BRDF-uncorrected EVI has an overall range from 0.43 to 0.52, while the range of the BRDF-corrected EVI is higher, from 0.51 to 0.6. Additionally, the overall form of the mean ‘greenness’ trends for the indices differ. The variation in the BRDF-uncorrected EVI, for instance, is more or less flat between January and July, after which it starts to increase, while the BRDF-corrected EVI has peaks in both April and September, with the latter peak being larger. FCOVER shows a distinct pattern reaching a minimum value in May and a maximum in October. Nevertheless, there is a clear correlation between the two VIs (coefficient of correlation of 0.69).

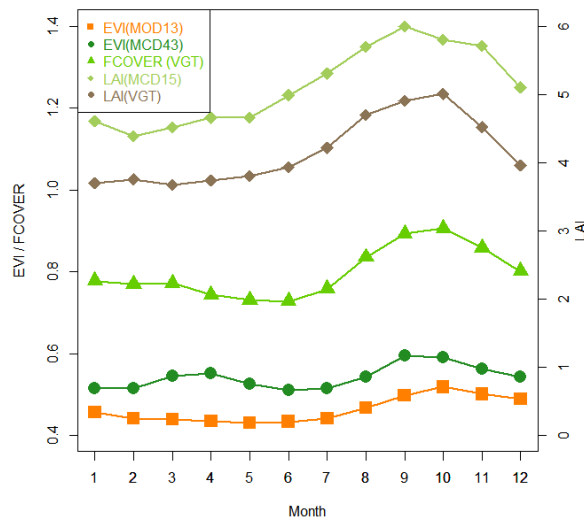


Figure 34. Mean monthly variation in the different VIs, at the scale of French Guiana. Note that, unlike EVI (MCD43) and FCOVER, EVI (MOD13) is not corrected for BRDF effects, while LAI is, by the way it is estimated, insensitive to BRDF effects.

Statistical analysis reveals that there are significant differences between the median FCOVER estimates for the wet season (December to July) and the dry season (August to October) - see **Figure 35**. (In that figure, the months which share the same letter such as January-July are not significantly different.)

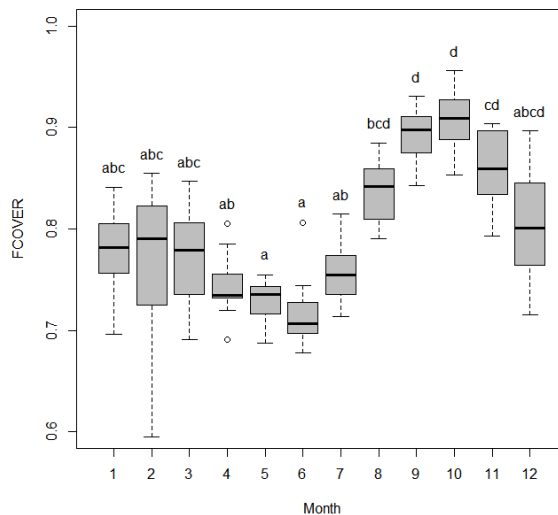


Figure 35. Monthly variation in FCOVER at the scale of French Guiana. Similar letters indicate that the FCOVER values are not significantly different, as the Kruskal-Wallis comparison test was not rejected at the 0.05 significance level.

Overall, the median FCOVER values for the months of September and October are significantly higher than the wet season months (Kruskal-Wallis test; P -value < 0.05). Similar trends are revealed in analyses of the EVI and LAI data, with the EVI data also showing September and October's median values to be significantly different overall from the wet

season months. For the LAI data (from both MODIS and VGT), August, September and October have significantly higher values than the wet season months, in general (results not shown).

VI variation at the site-level

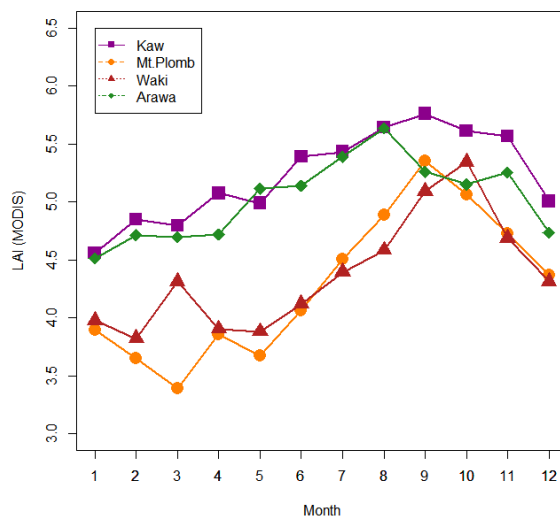


Figure 36. Mean monthly MODIS-derived LAI variation at the 4 sites in French Guiana.

In terms of the site-level analysis, clouds caused large data gaps in the wet season data for EVI, and VGT-derived FCOVER and LAI. Hence, the only index for which a full archive for all sites could be generated was the MODIS-derived LAI (**Figure 36**). While LAI for the 4 sites is shown to display an overall trend similar to that for all of French Guiana, the differences in trends between sites are quite pronounced, and that to (i) magnitude, (ii) greenness peaks, and (iii) overall form of the trend. For instance, in terms of the overall form of the trend, for both Montagne Plomb and Waki, the trend is steeper, suggesting a greater distinction in leaf flushing between the earlier and later parts of the year, compared to the Arawa and Kaw sites. More significantly, the timing of greenness at each of the sites is different. For example, the data indicate that for both Montagne Plomb and Kaw, the peak of greenness is in September, while for Arawa, the peak is a few months earlier, in July, and Waki has its peak greenness in October. While there is some overlap in terms of the magnitude of LAI, overall, the ranges are distinct. For instance, in Montagne Plomb the LAI ranges from 3.39 to 5.35, while for Waki, LAI ranges from 3.82 to 5.34. The ranges of LAI for both Arawa and Kaw is overall higher than that of the other two sites, with Arawa’s LAI ranging from 4.51 to 5.63, and Kaw’s being the highest overall LAI range, from 4.56 to 5.76.

Using Kaw as an example, it can also be seen that there is a great deal of month-to-month variance in terms of the LAI estimates (**Figure 37**). A closer examination of the LAI data indicates that Kaw’s peak greenness, mainly occurred in September (e.g. 2003, 2006, 2007, 2008, 2009, 2012, 2013), but in some years (2002, 2004, 2005, 2010, 2011), that peak shifted a few months earlier or later. The seasonal trends are also confirmed by statistical analysis. In the case of Kaw, for example, the LAI values in the period August to November are significantly higher than in the wet season. In the case of Montagne Plomb, overall, the LAI values for August through October were significantly higher than the wet season months, while for

Waki, only September to October had significantly higher LAI. In the case of Arawa, statistical analysis indicated that only during the month of August were LAI values significantly higher than in the wet season months of January and March.

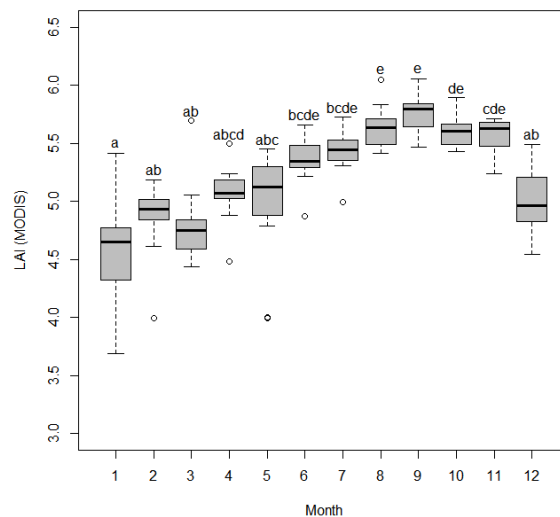


Figure 37. Monthly variation in MODIS-derived LAI at the Kaw site. Similar letters indicate that indicate that the LAI values as not significantly different, as the Kruskal-Wallis comparison test was not rejected at 0.05 significance level.

Discussion

I. Evaluating BRDF impacts on VI temporal variation at the regional scale

While earlier studies have examined variation in VI trends for tropical forests in zones covered in this study, they did not examine potential BRDF impacts on VIs (Bradley et al. 2011; Pennec et al. 2011). While this study thus sought to evaluate the influence of BRDF on VI data, it did not find strong correlation overall (i) between the VIs from the different regions, or (ii) between intra-annual variation in solar elevation and the VIs (except for central Africa, in the case of EVI and LAI). Had VI variation been principally caused by BRDF, one would have expected the VI patterns to be similar to the solar elevation pattern in the three zones. As that was not the case, the observed variation in the VIs is likely not principally due to BRDF. While sensor view angle also contributes to BRDF effects, for this study, that is a moot point, as the input data for EVI and FCOVER were nadir normalized (Morton et al. 2014; Camacho et al. 2009; Schaaf et al. 2011; Liu 2003). Also, the VIs –developed independent of each other – illustrate similar trends, and are generally highly inter-correlated.

Each of the three regions also displayed distinct, annually recurring trends, which differ not only in when they peak, but also in the magnitude of the changes across the year. Central African forests display the greatest range of values, whereas that range is smaller in the Guiana Shield, and the variation in northern Borneo forests is low. As VIs are surrogates for photosynthetic activity, this would seem to imply that forests in the three regions behave distinctly, although the question is why (Balzarolo et al. 2016).

For instance, it might be that the observed variation in the VIs was due to atmospheric contamination of the satellite data (hypothesis 2) instead of being the result of mere variation in solar elevation (hypothesis 1). To that end, the regression models were helpful in explaining the observed variation in the VIs and testing those hypotheses. For the Guianas and central Africa, depending on the VI evaluated, the 'atmospheric' models had R^2 values ranging from 0.14 to 0.52 for the former region, and 0.31 to 0.63 for the latter. These may suggest some level of atmospheric contamination of the VI data (particularly for central Africa). For central Africa, it is documented that there is extremely persistent cloud cover due to the movement of the inter-tropical convergence zone (ITCZ), potentially affecting the satellite signal (Maloba Makanga and Boko 2000). Also, for central Africa, the atmospheric artefact of cloud cover was also highly correlated with precipitation, which was the single driver with the greatest predictive power. While forests in central Africa appear greenest when there is a high degree of cloud cover, they are also the greenest during the period of most rainfall. However, regardless of potential atmospheric contamination, the environmental factors overall possessed greater explanatory power than other factors.

As such, for both the Guiana Shield and central Africa, it was demonstrated that variation in the VIs were better explained by environmental factors than by solar elevation or atmospheric effects (e.g. $R^2 > 0.7$ for EVI). The observation that the environmental factors possess more explanatory power than other factors is likewise supported by comparison of such models with models using all 8 explanatory variables. In the case of FCOVER, for instance, the inclusion of solar elevation, AOD, and cloud cover along with the environmental variables only increased the explanatory power from 0.65 to 0.69 for the Guiana Shield, and from 0.73 to 0.84 for central Africa.

As most of the VI variation is not explained by BRDF or atmospheric contamination, this would suggest that the satellite signal represented by the VIs does manage to capture actual variation in the forest canopy (i.e. phenology), although this warrants field validation. The VI data would nonetheless suggest, for instance, that the tropical evergreen forests of the Guiana Shield have peak 'greenness' when more solar radiation is available in the months of September-November (Bi et al. 2015; Bradley et al. 2011; Huete et al. 2006). In contrast, in central Africa forests appear to 'green up' when both solar radiation and rainfall are at their highest, in May and September. That is, forest phenology in different regions may be synchronized to different factors, and the correlation analysis indicates that driving factors differ greatly between central Africa and South America. A recent study found that tropical photosynthetic activity is only bound to precipitation when precipitation is less than 2,000mm/year – only the case for central Africa, but not the Guiana Shield or Borneo (Wagner et al. 2016). Other studies suggest that in the Guiana Shield, the phenological cycle is matched to the availability of light (Bi et al. 2015; Huete et al. 2006; Saleska et al. 2007, Sabatier and Puig 1986).

In the case of Borneo, the regression models had little explanatory power. This is unsurprising given the weak seasonal signal observed in VIs, which might explain the low model fits. It might be that atmospheric contamination of the data has affected the sensors' ability to observe variation. However, another possibility is that the quality of the explanatory datasets may differ by region. That warrants further exploration, as well as investigating whether other equatorial evergreen forests display similar VI variation.

II. Evaluating BRDF impacts on VI temporal variation at the plot level

Degree of sensitivity of EVI to solar direction

An earlier study utilized drone imagery over Guyana to demonstrate that EVI varied with the time of data acquisition (Brede et al. 2015). Using radiative transfer modelling, the present study has expanded upon those findings, by being able to characterize the sensitivity of EVI to solar direction (i.e. solar elevation and azimuth), across a range of time-scales, including EVI variation on days with very different solar configurations (i.e. 15 September and 15 December), and EVI variation across the year. This probably comes as no surprise but highlights that a degree of caution should be exercised when comparing EVI estimates acquired at different dates, because the differing solar elevations will lead to spurious differences in EVI. In other words, it has been concretely demonstrated that the same area of forest will indeed reflect light differently depending on changes in solar elevation and azimuth, independent of any real change in vegetation structure. This does not, however, signify that remote sensing data cannot at all be used for examining changes in forest structure, as will be elaborated on. And in terms of the absolute sensitivity of EVI to changes in solar elevation, although it may seem minuscule, at Paracou, EVI was demonstrated to increase by between 0.0006 and 0.0010 for each degree increase in solar elevation. However, at Itoupé and Nouragues, increases in EVI were larger (0.0013 and 0.0017, respectively), perhaps owing to differences in inclination or canopy roughness.

Degree of sensitivity of EVI to LAD

Beyond demonstrating the high sensitivity of EVI to solar direction, this study has likewise explored the sensitivity of EVI variation to variations in leaf angle distribution (LAD), and has shown, for instance, the degree to which EVI based on a planophile distribution is expected to differ from EVI based on an erectophile distribution. For instance, EVI estimated assuming a planophile distribution is 12.8% higher than EVI estimated based on an erectophile distribution, 9% higher than EVI assuming a spherical LAD, and 3.5% higher than EVI assuming plagiophile LAD. The LAD of the vegetation is thus of particular importance due to the possibility that changes in EVI could be triggered by hydrological stress-related changes in LAD instead of real phenological variation. While a potential model of LAD change was not employed in this study, it can reasonably be hypothesized that if forests in French Guiana exhibit erectophile LADs in the dry season months of August to October to cope with drought stress, this would cause a dip in EVI for those periods. On the contrary, the satellite data indicates that EVI is increasing in the dry season rather than decreasing, so the hypothesis may not be so reasonable.

EVI and forest structure

In addition to the previous findings, it was also observed from the modelling that EVI differed between the three sites studied, and it is useful to understand why that is. It was demonstrated that Paracou had the highest EVI of the three sites (mean of 0.49), followed by Nouragues (0.47) and Itoupé (0.46). This order appears to be based on the density of vegetation (as expressed by the PAI). In fact, various studies have suggested that vegetation indices like the

Enhanced Vegetation Index (EVI) and the computationally similar Normalized Difference Vegetation Index (NDVI) are proxies for vegetation density, with higher quantities of leaves leading to higher vegetation index estimates (Huete and Justice 1999; Tucker 1979). It is interesting to note, however, that while the Paracou plot's mean PAI was 23.1% higher than that of Itoupé, its EVI was only 6.7% higher. However, while the PAI of the Paracou plot was only 0.8% higher than that of the Nouragues plot, Paracou's EVI was 3.4% higher. Also, the Nouragues plot's mean PAI was 22.2% higher than that of Itoupé, but its EVI was only 3.2% higher. This indicates a disparity in terms of how PAI correlates with EVI.

Other factors that appear related to the distinctions in EVI across the three sites are the relative roughness of the canopies, and topographic slope. Thus, related to its canopy closure, Paracou also appears to have a smoother canopy than say, Itoupé, and that relatively smooth canopy is also indicated by various characteristics such as the mean canopy height slope (43.1 degrees at Paracou but 63.3 degrees at Itoupé), and the standard deviation of the digital surface model of both sites (4.8 for Paracou, and 16.8 for Itoupé). Nevertheless, as it is already known that canopy roughness will cause increased shadowing which will lower near-infrared (NIR) reflectance, it may be that the interaction of these has led to lower NIR reflectance at Itoupé (23.35%) than at Paracou (25.22%). And to some degree, topographic shadowing of the Itoupé plot may further be lowering the plot's NIR reflectance. Nevertheless, additional radiative transfer simulations would help to clarify this (e.g. whether a smoother canopy at Itoupé would lead to a higher EVI than Paracou's). All in all, this study has also been useful in pointing out how subtle differences in forest structure may influence EVI. It is also suspected that Nouragues plot's more open canopy compared to Paracou led that plot possessing lower EVI estimates, even as both plots had comparable mean PAI values (13.3 for Paracou versus 13.2 for Nouragues).

Solar direction variation or phenological variation?

The argument had been made in at least one previous study that the observed variation in vegetation indices like EVI in the greater Amazon may really be an instrumental artefact related to bi-directional effects (Morton et al. 2014). And in follow-up to that, and to findings from other studies (Brede et al. 2015), this study has gone to particularly great lengths to quantify the sensitivity of EVI to the bi-directional effects caused by the variation in solar elevation, particularly as such sensitivity relates to distinctly structured evergreen tropical forests (Brede et al. 2015; Nagol et al. 2015). While it is indeed demonstrated that solar elevation will influence EVI – between 0.0006 and 0.0017 points for each degree rise in solar elevation, depending on the site – the pattern that could be modelled assuming only variation in solar elevation does not match the pattern observed by sensors like MODIS. And it is suspected that the observed variation is not merely an observational error of MODIS as other efforts have demonstrated that at least for French Guiana, other sensors such as SPOT VEGETATION have noted similar intra-annual variation in vegetation indices (Cherrington et al. 2015b; Cherrington et al. 2016b). Put another way, if only solar elevation was driving the changes seen in EVI, then the observed pattern of EVI across the year would be different. In fact, EVI for the French Guiana plots – and any other tropical forest plots – would be similar to the trend in solar elevation, and have near-identical peaks in April and September. But this is not the case.

What this appears to suggest is that the vegetation structure is changing across the year, i.e. that French Guiana's forests really do display phenological variation, even as these forests are considered 'evergreen,' supposedly with phenology less pronounced than in deciduous forests. The hypothesis that phenological variation is partly driving the observed changes in EVI is supported by the results of the simulations in which the vegetation density at Paracou was allowed to vary in a similar fashion to the MODIS-derived estimates of LAI change. Hence, EVI variation based on the combination of both variation in vegetation density and solar elevation had a higher statistical correlation with the observed EVI variation estimated by MODIS (0.70) than when EVI variation was modelled on the assumption of no phenology (correlation of 0.46).

It should just be mentioned that it is also theorized that the change in EVI might alternatively be driven by another phenology-related aspect, that is, the sprouting of new leaves whose optical properties differ from older leaves. As such, an alternative hypothesis is that the observed peak in EVI in September may be driven by new leaves rather than an outright increase in PAI. This warrants further research, but was not assessed in the context of this study due to the absence of field data on changing optical properties of the foliage. Lastly, it has already been discussed how [non-phenology related] changes in LAD might contribute to seasonal changes in EVI, but it was noted that it would actually be expected that drought stress would suppress EVI in the dry season.

Applicability to other tropical rainforests

In terms of this Chapter's implications, it has contributed to understanding how vegetation indices such as the Enhanced Vegetation Index, EVI, are affected by factors such as leaf angle distribution, leaf area index / plant area index, solar elevation, and to a lesser extent, solar azimuth. Due to the use of varied forest structures and topographies, it is expected that the findings of this study can be applied to other tropical forest regions, as it is expected that EVI variation will be similar, albeit tempered by the reality that the further away from the Equator, the greater the difference in the variation in solar elevation. Nonetheless, this study's findings can be seen as a means of partly understanding EVI variation. Where variations in solar direction would be expected to result in peaks in both April and September (as seen in the simulated monthly EVI data), the actual data from MODIS reveal a different pattern altogether, suggesting changes which cannot merely be understood as due to changes in solar position. In that context, this study has also contributed to better understanding uncertainties in EVI estimation for tropical forests. It is also suspected that the magnitude of the changes modelled will, however, differ based on the openness of the forest canopy, and the forest plots used in this study had closed canopies.

In terms of the perspectives for further research, regarding the broader discussion and controversy surrounding whether vegetation indices like EVI can indeed be used to monitor the phenology of tropical rainforests, this study recommends the collection of further field data. Specifically, this study utilized ALS data acquired over the different sites during the dry season. To validate the hypothesis that there is some structural or spectral change taking place in these forests which leads to the change in EVI observed by MODIS, it would be extremely useful to collect more LiDAR data (aerial or terrestrial) over a regular period of time (e.g. monthly, over the period of a year). This would allow for conclusive verification of the

structural changes suggested by this study's radiative transfer modelling. While the phenocam studies (Lopes et al. 2016; Wu et al. 2016) indicate that phenological variation is indeed occurring in the Brazilian Amazon's evergreen rainforests, confirming whether or not such is the case for French Guiana should be a priority. That would shed light overall on the topic of phenological variation in evergreen tropical forests.

III. Assessing VI variation by forest type, using corrected data

This study has demonstrated that BRDF-corrected vegetation index data for French Guiana's forests demonstrate seasonal patterns. That is to say, at the scale of all of French Guiana, the data does show significant variation between the wet and dry seasons. A range of indices derived from multiple satellite sensors show, for instance, that the VI data for the dry season months of August to October are, in general, significantly higher than for the wet season months. Additionally, such variation is also evident at finer scales. While the results differ somewhat from an earlier study using data not corrected for BRDF, the seasonal pattern does not disappear with the BRDF corrections. The implications of the findings thus warrant further exploration.

Differences in VI estimates

The VIs used differ in magnitude, and somewhat in the trends shown. It should, however, be recalled that the indices used represent different concepts, and have values with different scaling. For instance, the range of LAI values is typically 0-7, while both EVI and FCOVER have a maximum value of 1, representing a 100% cover rate (Baret & Weiss 2014). Furthermore, both EVI and FCOVER represent characteristics at the surface of the canopy (Camacho et al. 2009, Huete et al. 1999). LAI, on the other hand, is defined as "the ratio of leaf area to land surface area in a vertical column," essentially an indicator of the *quantity* of leaf material within a section of forest (Chase et al. 1996). Thus, it would be expected that LAI's estimates of leaf quantity, would be different than the gap fraction estimates of FCOVER, even if it is known that gap fraction influences total leaf area (Camacho et al. 2009, Baret et al. 2013).

It was also noted that while the LAI trends for both the MODIS- and VGT-derived estimates were similar, on average, the VGT-derived LAI estimates were 19% lower than the MODIS-derived estimates. A study over western Africa came up with similar results when comparing MODIS-derived LAI and VGT-derived LAI, but concluded that two factors likely caused it: (i) very different algorithms used to estimate LAI, and (ii) different product temporal windows, i.e. MODIS' 8-day window compared to the VGT LAI 30-day window (Gessner et al. 2013). Nevertheless, while the VGT-derived LAI estimates are overall lower than the MODIS-derived estimates, correlation analysis did indicate that their month-to-month variation is similar.

BRDF corrections

An important point to emphasize is that data which was (a) corrected for BRDF, (b) generated independently from different satellite sensors, and (c) generated from distinct algorithms, indicate a dry season 'green-up' in French Guiana. This may seem to be contrary to results from recent studies questioning the Amazon green-up findings derived from BRDF-affected VIs (Morton et al. 2014). One commentary even referred to the Amazon green-up findings as a "green illusion" (Soudani & François 2014). Dry season green-up may even seem counter-intuitive, because as stated in one earlier study, for "Amazon forests... [such green up is] opposite to ecosystem model predictions [indicating] that water limitation should cause dry season declines in forest canopy photosynthesis" (Huete et al. 2006).

Nevertheless, it should be recalled that the recent studies have not said that Amazon green-up is not occurring, but rather that with data not corrected for BRDF, it could not be established (Morton et al. 2014, Soudani & François 2014). Thus, in the present study, BRDF-corrected data was used to examine the issue of green-up, and even with BRDF-corrected data, strong seasonal patterns are evident. In other words, the seasonal patterns which were detected in the earlier study of VIs over French Guiana's forests were not necessarily artefacts (Pennec et al. 2011). It also bears repeating that the seasonal patterns were evident across different VIs, as well as across different types of forest in different sites. It should also be noted that the BRDF-related study focused on a different part of the Amazon, and it may well be that patterns there differ from further north, in the Guiana Shield (Saleska et al. 2007, Bradley et al. 2011, Morton et al. 2014). And if there were any doubts regarding the BRDF corrections, it should be recalled that the MCD43 source data was validated in a global study that looked at albedo estimates for a range of sites, including the flux tower in French Guiana (Cescatti et al. 2012).

Field and other evidence of phenological variation

If it can be accepted that the VIs do indeed demonstrate seasonal phenological variation in French Guiana's forests, it begs the question regarding whether field data support such findings. Previous studies do actually support the idea that French Guiana's forests are, to some degree, seasonal (e.g. Sabatier 1985, Sabatier & Puig 1986, Wagner et al. 2013, Fayad et al. 2014). For instance, one recent study used space-based light detection and ranging (LiDAR) data to show changes in biomass across the wet and dry seasons, in selected plots in the south of French Guiana (Fayad et al. 2014). Another showed a seasonal pattern to litter production in Paracou in northern French Guiana, with peaks between late August and mid-September, which, when compared to field estimates of LAI for the same site, suggests increased leaf production during that time frame (Wagner et al. 2013). The findings of other, earlier studies also point to leaf flushing in the dry season (Sabatier 1985, Sabatier & Puig 1986).

VI increases signify leaf flushing?

It has been demonstrated that VI estimates for French Guiana are significantly higher in the dry season than in the wet season. What those findings mean in terms of actual changes on the ground remains unsettled, for lack of concrete field data to confirm the findings from the satellite data. However, in light of the findings of the previous studies looking at phenology,

and in light of what is known about VIs, a hypothesis emerges. Overall, the VIs indicate a dry season increase in photosynthetic activity, while the increase in satellite-estimated LAI would point to an increase in the leaf surface, i.e. leaf-flushing. Thus, the likely explanation would be that the dry season ‘green-up’ observed by the satellites is an increase in leaf flushing.

Patterns vary by forest types

The second research question of this study sought to determine whether the VI trends observed at the scale of all of French Guiana ‘held’ at local scales. The reasoning behind that question was the idea that the overall, French Guiana-wide patterns might merely be due to the spatial averaging of patterns which vary by zones. It has been shown, however, that such is not the case, as the site-level patterns are generally similar to the French Guiana-wide patterns. Nevertheless, it has also been observed that the timing of green-up does vary between sites. The cause for such variation warrants further investigation, as local variations in VIs may be due to local variations in environmental conditions (e.g. differing light availability or soil moisture). Nevertheless, one observation is that the species composition of the 4 sites was known to differ. For instance, the Kaw site was dominated by mangrove species like *Avicennia germinans* (black mangrove) and *Rhizophora mangle* (red mangrove), while the Waki site was dominated by Parinari trees (*Parinari campestris*). A simple hypothesis is that the phenology (represented by the VIs) varies by species composition.

The findings presented here ultimately warrant validation in the field to test some of the hypotheses proposed (e.g. that the dry season increase in VIs is caused by real leaf flushing). The factors driving the observed patterns should also be considered. For instance, some studies explored how hydrology (soil water availability) influences the distribution of tree species in French Guiana (e.g. Pélissier et al 2002). One idea is that perhaps the timing of the greening of French Guiana’s forests is linked to soil water availability, which could carry a lag with rainfall. One recent study suggested that in some parts of the greater Amazon Basin, there is a lag between rainfall and vegetation response, and that lag could be due to the underlying hydrology (Bradley et al. 2011). While it was not explicitly addressed in this study, the pattern in the vegetation indices seems to align with the climate seasonality in the form of the amount of available radiation. That also merits further research.

IV. Synthesis

Taken into context, the main findings of this Chapter’s three main sections are as follows. Bi-directional effects would be expected to exert similar impacts on forests at the same latitude, yet a regional-level assessment indicates that forests in French Guiana exhibit different patterns of temporal vegetation index variation than forests in central Africa or northern Borneo. Further, that intra-annual variation is linked to the availability of solar radiation, supporting the findings of studies like (Bradley et al. 2011). In contrast, at the plot level, one sees that temporal variation only due to BRDF would be identical in terms of pattern, across different forest structures, and would be bi-modal, following variation in solar elevation. Yet, this is not what is observed in satellite data, which possess a distinct trend, suggesting that BRDF is not the cause. And as the previous two studies have supported the notion that vegetation indices can be used for evaluating phenological variation, this study likewise illustrates that patterns of VI variation differ greatly by forest type.

Where there has been a vigorous scientific debate and controversy regarding, in essence, the applicability of remotely sensed spectral reflectance data and derivatives to monitoring forest phenology in the tropics (Huete et al. 2006; Saleska et al. 2007; Samanta et al. 2010; Samanta et al. 2012; Morton et al. 2014; Soudani and François 2014; Hilker et al. 2014; Bi et al. 2015; Xu et al. 2015; Saleska et al. 2016; Wu et al. 2016; Lopes et al. 2016), the sections of this Chapter have sought to weigh in by examining the extent to which bi-directional effects (instrumental artefacts) affect data for French Guiana. And using French Guiana as an example, it has been demonstrated with radiative transfer modelling that BRDF-driven apparent temporal variation would essentially look quite different from what has been observed by satellite sensors such as MODIS (or by VEGETATION).

On the other hand, radiative transfer modelling has also shown that if BRDF is the prevailing influence in terms of vegetation variation, then the variation among different forest types should be similar, at least in terms of the overall patterns of variation. Taking that further, if BRDF is what drives VI variation in the tropics, and not actual phenological variation (e.g. leaf exchange, leaf flushing), then despite differences in forest structure across continents, VI variation in central Africa should still mirror that of the Guianas, and both VI variation patterns should closely mirror the pattern of variation of solar elevation. However, the first section of this Chapter indicates that such is not the case, since VI variation across the different regions differs significantly, suggesting that the VI variation is not actually driven by BRDF.

And as such, the first two sections of this Chapter have taken different approaches to addressing the same issue, i.e. whether the intra-annual variation of VIs is merely an artefact, or something more. And both approaches coincide in suggesting that the variation is not merely an artefact, and the first section's findings likewise coincide with the findings of other studies which have likewise reached the same conclusion, that Amazonian forests green up to take advantage of the increased availability of solar radiation in the dry season (Bradley et al. 2011; Hilker et al. 2014; L. Xu et al. 2015; Bi et al. 2015).

Further, the cross-continental findings of the first section of this Chapter are mirrored in another study which comes to the conclusion that the link between vegetation indices and rainfall observed in central Africa, for instance, is a biological consequence of forests whose mean annual rainfall is below 2,000mm (Wagner et al. 2016). And in terms of the broader ecological implications of this Chapter, the main implication of the first section is the suggestion that forests in different regions are linked to different factors. As such, in the Guianas, the pattern of VI variation is most linked to radiation (light dependency), while in central Africa, that pattern is linked most to rainfall (rainfall dependency). So in terms of limiting factors, it is logical that where water availability may not be the limiting factor for forests in the Guianas, forests' phenological cycles would thus be tied to other variables such as radiation.

The Chapter's third section, in turn follows the indications of the preceding studies, that BRDF is not driving vegetation index variation in French Guiana to in turn interpret the intra-annual variation patterns in the context of different forest types. This is essentially a re-creation of an earlier study, albeit with a different scope (Pennec et al. 2011). In contrast to the earlier study, what is demonstrated is that different forest types actually green-up differently, in terms of timing and the magnitude of the estimated green-up peaks. As such, the mangrove forests of

the Kaw region demonstrate more robust satellite-derived LAI estimates than do the Parinari-dominated forests which appear to have a stronger seasonal pattern across the year. And these seasonal patterns do not conflict with, but support the findings from earlier field studies (Sabatier 1985; Sabatier and Puig 1986; Fernandes 1999; Wagner et al. 2013; Balzarolo et al. 2016). Further, as will be explored in the following Chapter, as the different forest types are shown to have different ‘temporal signatures,’ it is theorized based on the study that it might be possible to differentiate forests just on the basis of their temporal signatures (rather than their spatial spectral signatures).

Nevertheless, altogether, this Chapter’s three related sections complement each other in providing different perspectives on the issue of temporal variation of tropical forests, from a broad-scale regional approach which crosses continents to a finer approach which examines large forest landscapes within French Guiana itself, to simulations at the scale of 1 hectare plots. Whereas the studies relying on the satellite-derived vegetation index estimates might be susceptible to averaging values across large areas, the middle section of this Chapter focused on disentangling the satellite signal (in this case simulated), by using fine scale forest mock-ups to better understand how reflectance is affected by the interactions of overall vegetation density (as estimated by the plant area index, PAI), canopy roughness, canopy closure, and solar direction. In that sense, the Chapter’s middle section shed a great deal of light on patterns which might otherwise be seen as black boxes in terms of their complexity. And the insights gleaned in turn owe to the pioneering work in radiative transfer modelling (Gastellu-Etchegorry et al. 2003; Gastellu-Etchegorry et al. 2012; Gastellu-Etchegorry et al. 2015).

While being able to conclusively determine what is driving French Guiana’s VI variation is somewhat illusive, the three studies together aid in the process of deduction about what must ultimately be occurring in French Guiana’s forests. New, more specific research questions are in turn generated through the process, such as:

- Can seasonal changes in canopy-level leaf biochemistry due to dry season leaf flushing explain the satellite-observed seasonal variation in spectral reflectance in French Guiana’s forests?
- To what extent do seasonal changes in vegetation density explain the satellite-observed seasonal variation in spectral reflectance of French Guiana’s forests?
- How do leaf angle distributions actually change inter-annually across French Guiana’s forests, and to what extent could those changes contribute to the observed vegetation index variation?

Those questions were not addressed in the scope of this PhD thesis but nonetheless serve as areas of interest for future research, particularly the ways in which canopy-level biochemistry affects canopy spectral reflectance, and the influence of changes in vegetation density, and in leaf angle distributions. All three of these represent unknowns with regard to the reflectance of French Guiana’s forests, and as such certainly warrant further attention.

Chapter 3: Patterns of spatio-temporal variation in tropical forests

Introduction

As indicated in the General Discussion, characterizing the patterns of spatial variation of tropical forests is of significant interest in the study of ecology (Chave 2008). While remote sensing provides tools for characterizing that variation, as indicated in the previous chapters, it can also be appreciated that such characterization is not without significant challenges, due to instrumental and other artefacts. But instead of focusing on characterizing forest typologies, up until now, much attention has remained focused on mapping forests as large undifferentiated blocks, mainly for the purpose of merely mapping deforestation-related changes in forest cover (Cord et al. 2013; Hansen and Loveland 2012). Even so, the identification of forest types is necessary for a range of applications, from forest conservation gap analyses to climate change mitigation efforts (Tallis et al. 2013). Less than a decade ago, the potential of the use of remotely sensed observations for identifying plant functional types was highlighted in a perspectives study (Ustin and Gamon 2010). While that study pointed out how information on forest structure, canopy biochemistry, and phenology could be combined for a greater understanding of forests, to date, not many studies have followed the prescribed approach (e.g. Huesca et al. 2015).

Nevertheless, in tropical territories such as French Guiana, where there are gaps in knowledge regarding forest types, the concept of using novel techniques for determining forest types based on their ecological patterns remains relevant (Gond et al. 2011; Guitet et al. 2015). The potential of such approaches ultimately seizes on two concepts: (i) that tropical forests exhibit a high degree of spatial variability, and (ii) that they also exhibit a high degree of temporal variability (Hammond and Kolasa 2014; Chave 2013; Ollier et al. 2003; Dessard et al. 2004; Ramesh et al. 2010). As such, such approaches also challenge traditional remote sensing approaches which have generally been implemented under the implicit assumption that the spectral response of vegetation captured from a single point in time can adequately represent forests' spatial variability (Lillesand et al. 2007; Ustin and Gamon 2010).

Table 15. Select long-term vegetation index time-series.

No.	Index name	Acronym	Source	Availability		Spatial resolution	Temporal resolution
1	Enhanced veg. index	EVI	MODIS	March	2000-present	463m	16 days
2	Fraction of available photosynthetically active radiation	FAPAR	MODIS	March	2000-present	1km	4 days
3			VGT	Dec. 1998-	present	1km	10 days
4	Fraction of green veg. cover	FCOVER	VGT	Dec. 1998-	present	1km	10 days
5	Leaf area index	LAI	MODIS	March	2000-present	1km	4 days
6			VGT	Dec. 1998-	present	1km	10 days
7	Normalized difference veg. index	NDVI	MODIS	March	2000-present	463m	16 days
8			VGT	Dec. 1998-	present	1km	10 days

In contrast to the sophisticated and data-intensive approach proposed in Ustin and Gamon 2010, a simplified approach to mapping tree communities in French Guiana can involve merely using data on phenological variation represented by vegetation indices (VIs) (Huete et al. 2002). As illustrated in **Figure 38**, in general, VIs of French Guiana already possess defined patterns of spatial variation. Furthermore, there is a range of VIs and which possess large temporal archives, and which are derived from satellite sensors with global coverage such as MODIS and VEGETATION (VGT), including the examples presented in **Table 15**.

This Chapter therefore explores the degree to which the use of spatial and temporal data can contribute to an ecologically-focused mapping of tropical forest types in French Guiana. The main objectives were to:

- i. Extract the temporal pattern of VI spatial variation using time-series analysis techniques
- ii. Map forest types based on the combined patterns of spatio-temporal variation
- iii. Relate the spatial pattern of VI variation to environmental gradients

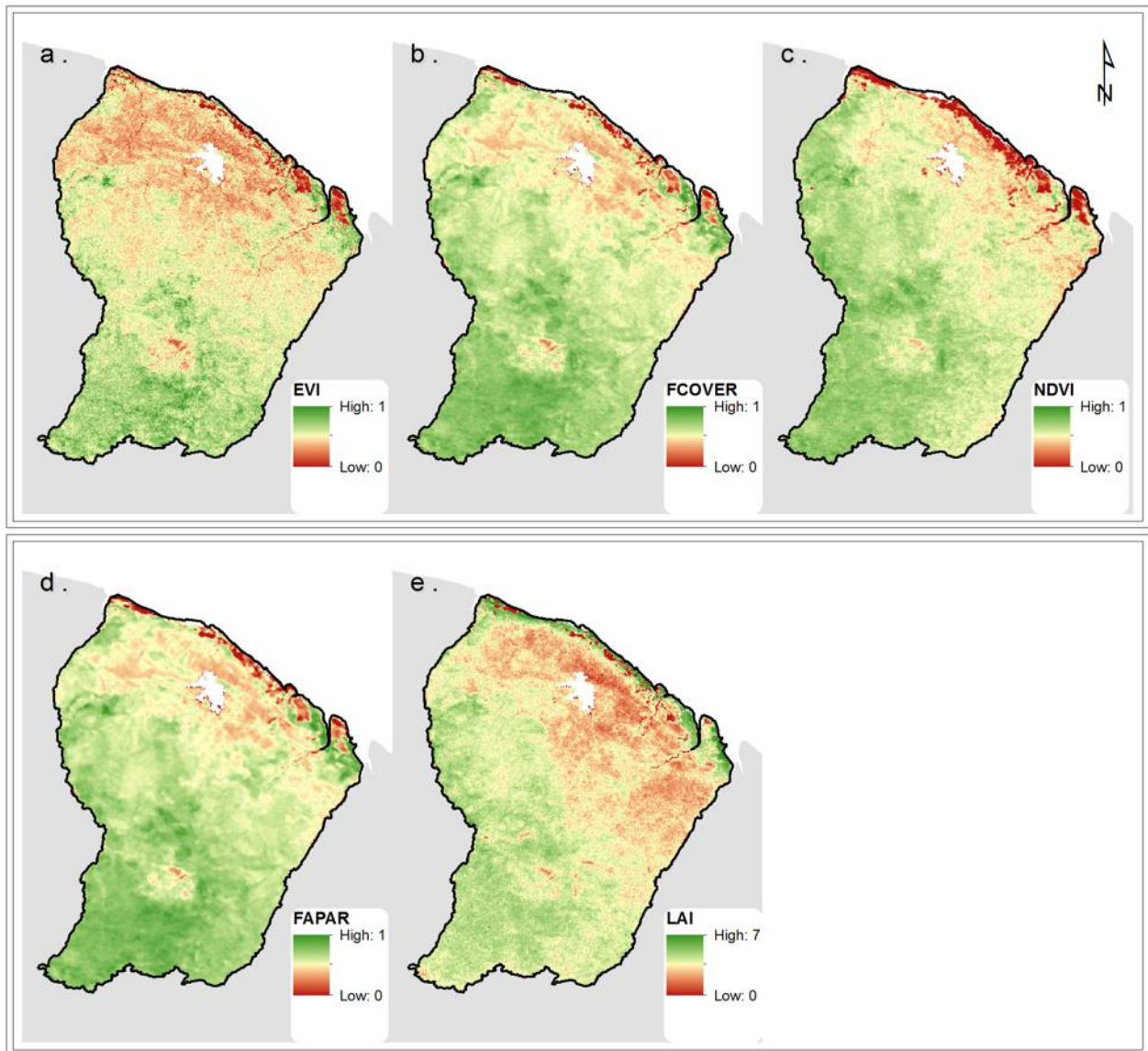


Figure 38. Patterns of spatial variation in the mean annual estimates of selected vegetation indices and variables, extracted for French Guiana: (a) MODIS-derived EVI, (b) VGT-derived FCOVER, (c) VGT-derived NDVI, (d) VGT-derived FAPAR, and (e) MODIS-derived LAI.

Results

Spatio-temporal variation of EVI

Figure 39 illustrates the spatio-temporal variation of EVI, or how the spatial pattern of EVI varies across the year, according to the seasonal pattern extracted from the time-series analysis. It is complemented by **Figure 40**, which likewise indicates that overall, EVI in French Guiana is highest in October (according to the median), although EVI values in September are nearly as high. In terms of the patterns of spatial variation themselves, it can likewise be observed that according to the time-series analysis, overall EVI values are lower in the north and northeast of French Guiana in the months of February, March, June, July, and August. EVI values in those areas represent one extreme, and they vary much more than in the south-

central part of the territory where EVI values appear more stable across the year (the other extreme).

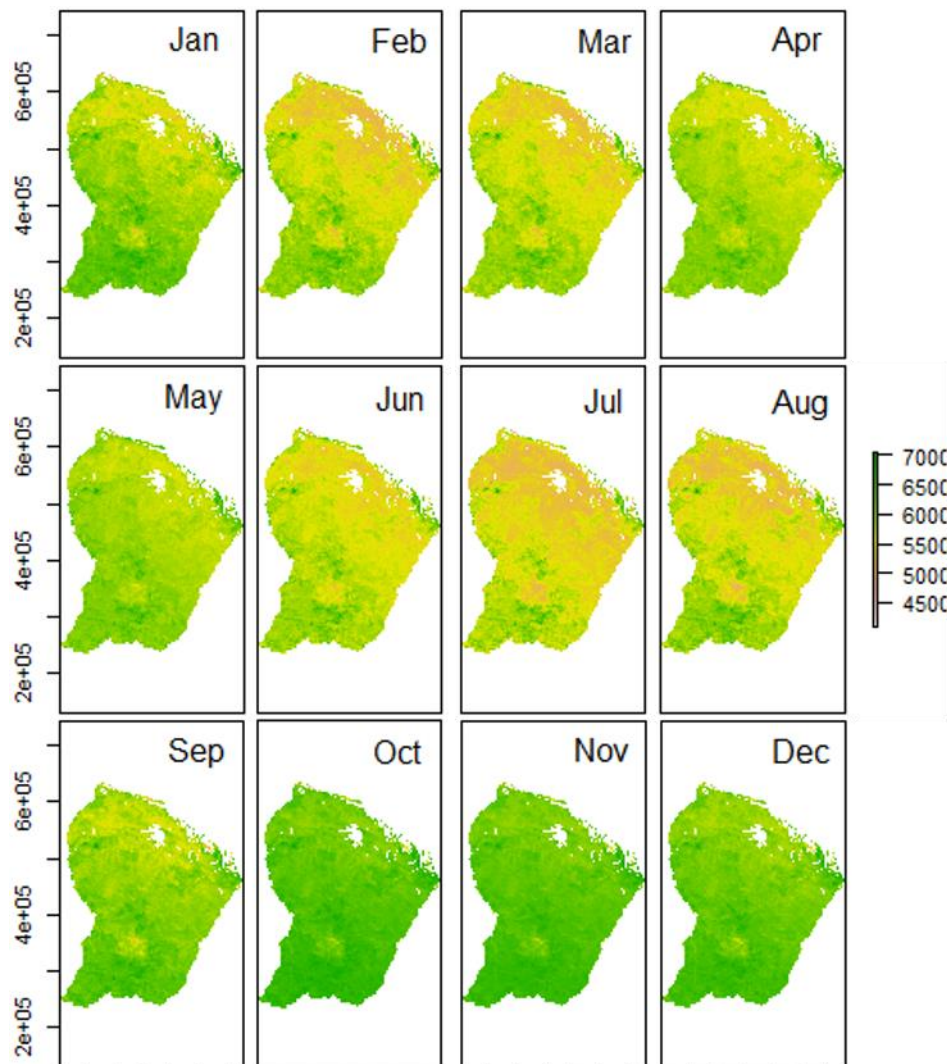


Figure 39. Monthly variation in the extracted seasonal pattern of EVI, derived from the January 2003 – December 2014 time series.

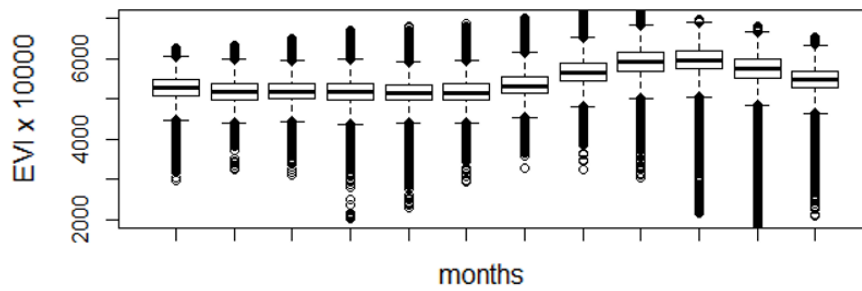


Figure 40. Boxplot of monthly variation in EVI for all pixels, based on the extracted seasonal pattern.

Forest types

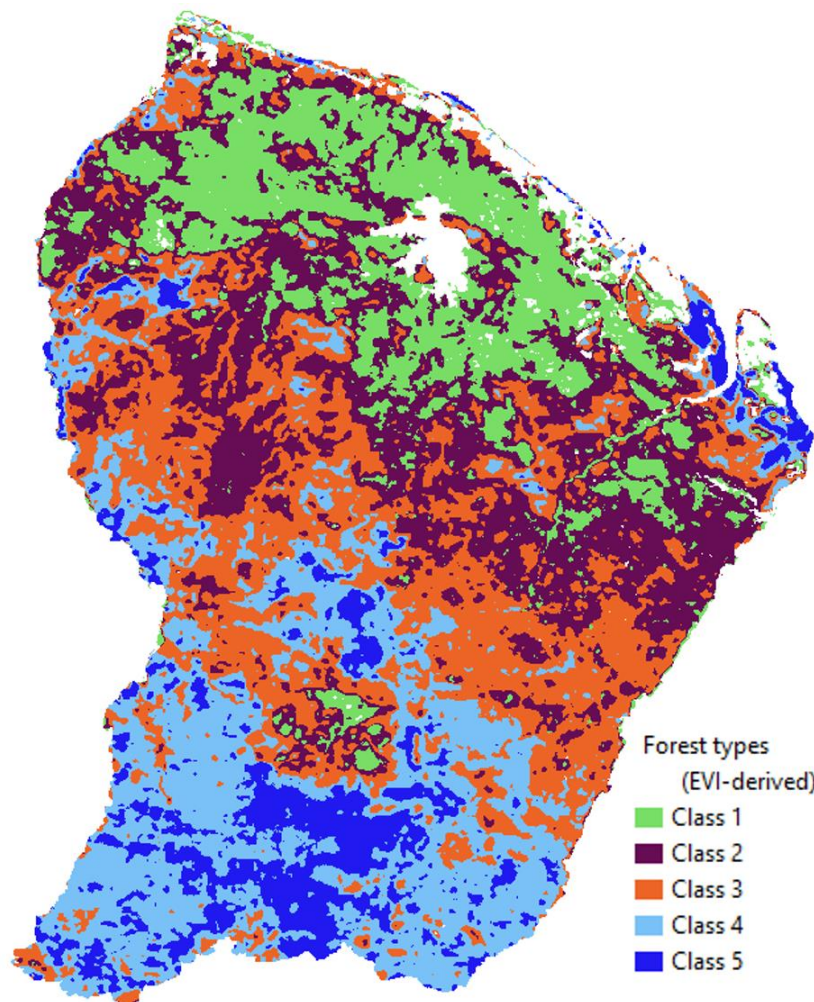


Figure 41. French Guiana forest types, based on spatio-temporal analysis of EVI time-series data.

The spatial distribution of forest types derived from spatio-temporal patterns are depicted in **Figure 41**, which is in turn based on the patterns illustrated in **Figure 39**. **Figure 42** in turn illustrates how EVI of each of the forest types varies across the year. For instance, class 1 is mainly restricted to the north of French Guiana, but also to the Parinari-dominated forests just south of the centre of the territory. The allegiance of both geographic blocks indicates that

both possess similar spatial and temporal patterns. As indicated in **Figure 42**, overall, class 1's EVI values are lower than those of the other classes. This is in contrast to class 5, which has the highest EVI values overall, but whose 'membership' is mainly restricted to the south, with the exception of mangrove forests in coastal French Guiana, and bamboo forests in the territory's north-western plateaus.

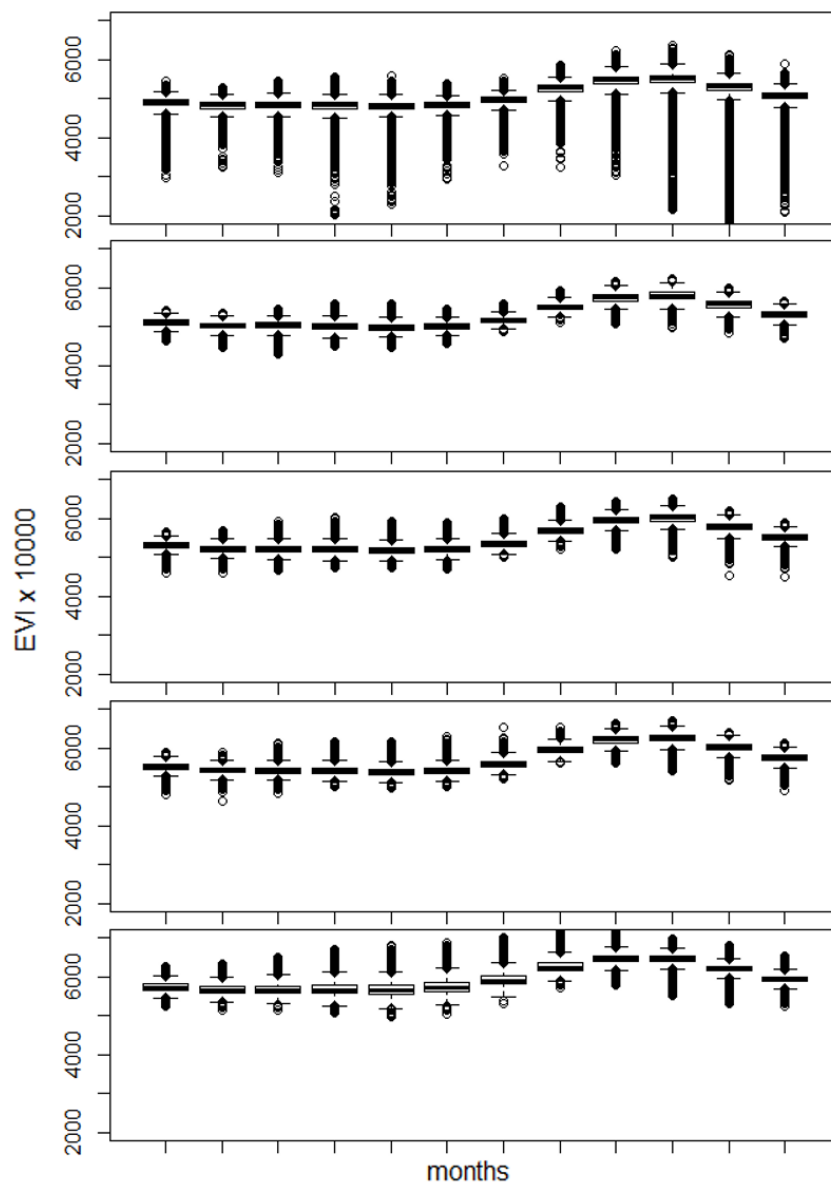


Figure 42. Boxplot of monthly variation in EVI for all pixels, based on the extracted seasonal pattern.

3.3 Spatial variation and variance partitioning

The results of the OLS regression of the first axis of the PCA of the EVI seasonal pattern against the 10 environmental variables are summarized in **Figure 43**, which illustrates that overall, the environmental gradients only explain 47% of the variation of EVI. Furthermore, topography explains only 32% of the variation, while climate explains 41% of the variation, with 26% of the variance consisting of the shared variance explained by both topography and climate.

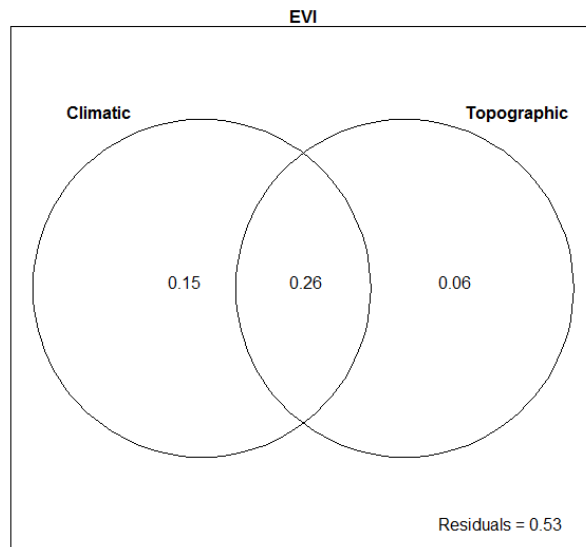


Figure 43. Variance partitioning with respect to how the different environmental variables (divided between climatic ones and topographic ones) explain the spatial variation in EVI.

Discussion

Comparisons with previous studies

This study contrasts with previous efforts from a conceptual perspective. Purely spectral classifications – like the traditional supervised classifications (e.g. Gond et al. 2011), do not, by the way they are formulated, consider the temporal dimension. In that sense, they do not necessarily reflect ecological patterns per se, whereas by contrast, spatio-temporal classifications, like the ones pioneered in this study do consider temporal variation (i.e. phenology), which, as explored in other studies (Cherrington et al. 2016b) likely results from the interactions of various environmental factors such as seasonally varying availability of sunlight or rainfall. To that extent, the map of forest types developed in the context of the present study differs spatially from the previous studies, although it must also be reflected that the method used to examine the input spatial data differs greatly from the earlier studies. As such, it would be expected that the results of this study would indeed differ from the earlier efforts of others (Gond et al. 2011; Guitet et al. 2015), which should therefore provide different perspectives on French Guiana’s forests. And that may be the value added by the present study is that it presents French Guiana’s forests through the lens of how forests not only vary in space, but how they differ in time.

Meanings of the classes mapped

It is speculated that the forest types mapped using the technique used in this study may serve as proxies for functional groups of plants, particularly in the way that the concept is explained in (Huesca et al. 2015). That is because unlike purely spectral traditional classifications, the groupings here are not based on spectral similarities which might likely signify groupings of species. (This may be a moot point for French Guiana where there is a high density of species per hectare and 1km data will therefore represent mixtures of signals of many species.) The phenological patterns revealed here would therefore tend to signify groupings of plants – at

a broad geographic scale – whose responses to climatic variation are similar. And to that extent, it is considered that this classification represents a truly ecologically consistent mapping of French Guiana’s forest types. Thus, the mangrove and wetland forests of French Guiana’s low-lying coastal fringe are indicated, via this analysis, to have similar patterns of spatial and temporal variation with high elevation bamboo-dominated areas in the northwest of the territory and Parinari forests (mapped as class 5).

Spatial variation of vegetation indices and explanatory factors

One of the main findings of this study is that just under half of the spatial variation of EVI correlates spatially with environmental gradients. It is anticipated that, to a certain extent, this may be due to errors in mapping the spatial variability of the explanatory variables. For instance, where the different explanatory variables were largely mapped using remote sensing, and such methods themselves are subject to instrumental errors, there exists the possibility that more spatial variability could be explained if the accuracy of the explanatory variables were improved. However, the incomplete fit might also reflect distinctions between the concepts of niche assembly and dispersal assembly (Chave 2009), with the environmental gradients serving as proxies for niches.

For instance, in the context of dispersal assembly (Chave 2009), it is expected that the distributions of forests will, to some degree, display the randomness of patterns of plant dispersal. Where the environmental gradients may allow for the mapping of niches (e.g. plants’ preferences for certain quantities of radiation, precipitation and temperature), it is obviously not so simple to map past patterns of plant dispersal. Thus, there will appear to be a randomness to the distribution of forests, but such randomness may simply reflect patterns that are not currently understood. The distributions seen may likewise reflect the effects of past patterns of disturbance which are not currently known. In other words, there may be underlying patterns even to what is now perceived as randomness in this way of mapping French Guiana’s forest types.

Potential validation

This study’s findings warrant further examination in the form of field validation. However, how one would go about field validating the temporal trends may not be so easy. Extraction of the five dominant temporal patterns – and these are produced by averaging patterns – indicates patterns which are differentiated largely on the basis of the degree of seasonality (**Figure 6**). Thus, without geographically distributed field observations of phenological patterns, it may be difficult to substantiate whether indeed the forests of one particular class are indeed distinct from those of another class. Further research could involve cross-validating the maps produced with other, existing maps such as those of (Gond et al. 2011) and (Guitet, Brunaux, et al. 2015), even as those were produced in different ways and it might be a case of comparing apples and oranges. Another means of further exploring the patterns seen might be the use of multi-temporal analysis of radar backscatter data, which is increasingly available due to the launch of the Sentinel-1A and Sentinel-1B satellites by the European Space Agency (Attema et al. 2009; Torres et al. 2012). Nonetheless, it might actually take years until there is a sufficiently large time-series with which to compare the VI time-series.

Further research

It goes without saying, however, that the work presented here is preliminary and future improvement on this work can be envisioned, using more temporally disaggregated data (i.e. finer time scales), and using higher levels of spatial detail. In that regard, it might be possible, for instance, to replicate this analysis on finer spatial and temporal scales. Where the present analysis was based on 463m x 463m MODIS data, the Proba-V VEGETATION sensor may offer a more suitable alternative than MODIS in that 300m x 300m (9 hectare) products are currently being generated, and 1 hectare products are also possible. This might thus provide for a better spatial characterization of French Guiana's forests.

Summary

Overall, this Chapter has served as a proof of concept that it is possible to map forests using both the spatio-spectral information and the temporal patterns. A map showing five dominant forest types based on spatio-temporal variation of EVI was generated for French Guiana, based on time-series analysis techniques used in combination with a 12-year archive of data. As this analysis is based on remote sensing-derived proxies for phenological patterns, it presents a novel way of mapping forests in an ecologically consistent manner, in contrast to traditional classification approaches.

General Discussion

I. Summary of findings

To frame this thesis' findings, it is necessary to re-examine the research questions which were posed at the outset of this document. This PhD project sought to address six inter-related research questions, presented below, with summaries of the responses to such questions.

- i. How does BRDF affect forest spectral response, and how does that ultimately impact estimates of forest type distributions?*

The first chapter of this thesis has demonstrated that the most commonly used source of reflectance data (Landsat) is indeed affected by bi-directional effects related to the sensor scanning angles. As such, reflectance data on the western portions of Landsat imagery appear (are viewed as) more sunlit than the reflectance data from the eastern sections of Landsat scenes. The result is that there is an across-track anisotropy in reflectance estimates, and this ultimately translates to biased estimates of forest types. To that extent, it can be considered that the research fully answered the first research question.

- ii. How do estimates of forest distributions change seasonally?*

It has been demonstrated that even when data are corrected for the bi-directional effects previously mentioned as affecting Landsat data, for instance, the evergreen forests of French Guiana exhibit a certain degree of seasonality in their reflectance. This is such that when forest types are mapped using such reflectance estimates, the distributions of forests appear to change from month to month. While it is possible that the distributions of the forest types mapped would vary somewhat from month to month based on the variation in shadowing produced by changes in solar direction, substantial changes in canopy reflectance would, on the other hand, tend to imply changes in forest structure and / or leaf optical properties. This is also linked to the findings regarding the fourth research question, which examined how the variation in solar direction alone affects canopy reflectance.

- iii. To what extent does observed regional-level variation in vegetation indices correspond to climatic variation or to atmospheric or instrumental artefacts?*

In follow-up to the third research question, this thesis has demonstrated that the regional-level variation in vegetation indices across tropical forests (particularly those in the Guiana Shield and in central Africa) is more correlated with seasonal environmental changes than with atmospheric or instrumental artefacts. Furthermore, contrasting the Guianas and central Africa, it has been demonstrated that the intra-annual variation in vegetation indices in both regions are correlated with different factors. Thus, where in central Africa, the trend in vegetation indices is highly [positively] correlated with precipitation, in the Guiana Shield, vegetation index variation is more correlated with the variation in incident solar radiation.

iv. To what extent can temporal variation in vegetation indices at the plot level be explained by solar direction variation?

Regarding the fourth research question, this thesis has demonstrated that at the level of forest plots, the variations observed with satellite sensors cannot be explained by seasonal variations in sun angles. Furthermore, it was also demonstrated that even forests with very distinct canopy geometries and densities should still demonstrate similar trends in vegetation index variation if solar elevation is the driver for vegetation index variation. Since this is not the case, it is implied that the vegetation index variation observed by satellite sensors must be due to structural and / or leaf optical changes.

v. Provided that the temporal variation in vegetation indices is not due to instrumental or atmospheric artefacts, how does such variation differ by forest type?

With regard to the fifth research question, it was demonstrated that when vegetation indices are corrected for bi-directional effects, at the scale of French Guiana, these indices display quite distinct trends (in magnitude and form) across different forest structures. This suggests that the intra-annual variation of such indices may be useful for discriminating between forest types. As follow-up, further research on how the temporal variation differs by the forest types mapped in previous studies (Gond et al. 2011; Guitet et al. 2015) is also warranted.

vi. How can combining spatio-temporal approaches improve forest type distribution mapping?

Regarding the sixth research question, this study has shown that, at least theoretically, it is indeed possible to map the distributions of tropical forests based on the distinct patterns in spatial and temporal variation, the latter which is an indicator of phenology. Nevertheless, within the scope of the research carried out, the research question could not be addressed as comprehensively as hoped for. While the method developed holds promise, there is much room for further improvement and further research.

II. Contextualizing the findings

It is necessary to consider the commonalities and contrasts among the findings of the different chapters, as well as how this thesis' findings fit into the context of previous studies. With regard to commonalities and contrasts, the following are of particular interest:

- BRDF's effects on both spatial data and time-series
- Spatial versus temporal detail in relation to forests
- The role of temporal data in forest type mapping

5.2.1 BRDF effects on spatial and temporal data

While the first chapter demonstrated how BRDF as a physical phenomenon affects estimates of spatial patterns such as the spectral reflectance of tropical forests, the second chapter focused on how BRDF also inadvertently affects time-series of spectral data and their

derivatives (e.g. vegetation indices). As such, BRDF was a uniting factor of the first two chapters of this thesis, and there were questions regarding whether or not it was even possible to contend with BRDF and really study spatial and temporal patterns of tropical forests. Fortunately, there has been over a decade and a half of research on the characterization of BRDF's effects on the data used (i.e. Landsat, MODIS, and VEGETATION) and so, to a great extent, for the course of this research, it was not necessary to reinvent the wheel, figuratively speaking (Danaher 2002; Schaaf et al. 2002; Baret et al. 2007; Baret et al. 2013). As such, in one of the studies in the second chapter, it was possible to focus on temporal variation of forests using BRDF-corrected data.

With regard to the issue of BRDF on reflectance estimates derived from Landsat, however, while a host of papers have been published on the topic of correcting Landsat data for BRDF, there is, as yet, no standard or even experimentally available BRDF-corrected Landsat product. (This is aside from a few 'corrected' image mosaics available from (Roy et al. 2010; Hansen et al. 2013), but the products available for French Guiana were found to be of low quality and thus unusable.) Thus, in the context of this thesis, it was necessary to develop a new methodology for BRDF correcting Landsat using the already corrected MCD43A4 product, with the basic elements of the correction methodology detailed in the second part of Chapter 1. So put in context, that specific study was the only of the recent French Guiana mapping exercises (Girou 2001; Gond et al. 2011; Guitet et al. 2015) to experiment with and successfully use BRDF-corrected reflectance estimates to map forest types in that territory. (To be precise, Guitet et al. 2015 did not map forest types based on reflectance, only the other studies.)

Nonetheless, it is interesting to point out that in contrasting how BRDF affects spatial data versus how it affects temporal data, in the case of the former, its effect is anisotropic reflectance along the scan path of satellite sensors (unless corrected for), as pointed out in the first part of Chapter 1. In the case of the latter, BRDF results in vegetation indices having spuriously high values when solar elevation peaks, as illustrated in the second part of Chapter 2. Thus, as indicated in that study, EVI estimates of a forest plot may change by between 9% and 14.8% during the course of a day, depending on: (i) the time of day, (ii) the day of the year, and (iii) the roughness of the canopy, among other factors.

5.2.2 Spatial versus temporal detail

In terms of how the sections of this thesis complement each other, it is interesting to note how spatial and temporal variation differ from each other, not only conceptually, but in their application to analyses of data on tropical forests' spectral response. Chapter 3 demonstrates, for example, that the satellite-derived estimates of Leaf Area Index (LAI) show strong seasonal patterns, i.e. strong temporal variation. But in contrast, such data in general does not display strong spatial variation, as indicated by the high Moran's I values which are indicative of spatial autocorrelation. As such, satellite-derived LAI estimates (at least from both MODIS and VEGETATION) display high clustering, with their values not apparently being very much differentiated by forest vegetation types.

Visual analysis also shows that the LAI values appear almost uniform across all of French Guiana, showing very little spatial detail. And this is despite the fact that the LAI products,

for instance, have the same nominal spatial resolution (i.e. 1km) as other vegetation indices used (Myneni et al. 1999; Huete and Justice 1999). In other words, even though different vegetation indices may have the same spatial resolution, it does not necessarily mean that they possess the same level of detail. However, it should also be noted that LAI is one of the products whose estimation is not as straight forward as other 'simple' indices like EVI (estimated using ratios of three spectral bands) and NDVI (estimated using ratios of two spectral bands). According to its documentation (Myneni et al. 1999), MODIS LAI, for instance, is estimated using a pre-defined map of forest cover types to assign LAI estimates per type, and it may be that this pre-defined forest type map is causing the spatial clumping of LAI estimates.

What is also interesting is that the MODIS LAI data, in theory, provided for the greatest level of temporal characterization of forest seasonality, as it possessed some 91 observations per year, which over 12 years equalled some 1,092 observations, versus the 144 observations (12 observations x 12 years) of the monthly MODIS EVI data used. Nevertheless, as the EVI data did not display the same spatial clumping problem that LAI did, EVI provided a better spatial characterization of French Guiana's forests.

5.2.3 Temporal data and forest type mapping

Across three different chapters, this thesis has examined the role of temporal data in forest type mapping. For instance, in the third part of Chapter 1, it was demonstrated that spectral reflectance-derived estimates of forest type distribution will change depending on the dates of the input reflectance data. It has largely been assumed that spectral reflectance should not change so drastically month-to-month (Guan et al. 2013; Xu et al. 2013) that the mapped locations of forests should change significantly. Nevertheless, while the concept of using 'anniversary' imagery (images taken at or around the same time of year) has been in practice, this study has concretely shown that French Guiana forests will be mapped differently between August and September, for instance. The study, in fact, used two different approaches to forest mapping (i.e. supervised and unsupervised spectral classification) to make that point. In the case of the unsupervised clustering of spectral classes, for instance, different numbers of statistically significant clusters were detected in different months' reflectance data (e.g. 37 clusters in August vs. 32 clusters in September). In the context of this thesis' other chapters' findings, what this suggests is that changes in forest structure (e.g. leaf-off conditions in canopy trees) and / or changes in canopy biochemistry (e.g. increased reflectance from new leaves) are driving the monthly variation in reflectance.

In contrast, what the third part of Chapter 2 indicates in terms of the role of temporal data and forest type mapping is that different types of forests possess different 'temporal signatures' in terms of their remote sensing-derived estimates of phenological variation. While the study did not assess such variation across all of French Guiana, choosing instead to focus on distinct forest types in four specific areas, it nonetheless suggests that it may be possible to map forests not only on the spectral differences evident in single dates of imagery, but also in terms of how forests vary across the year. That likewise laid the basis for Chapter 3, which focused on exploiting both spectral and temporal variations to discriminate forest types.

Chapter 3, when contrasted with the preceding chapters, suggests that forest types can indeed be discriminated using temporal signatures, although the relative accuracy of a multi-temporal approach versus a single date approach could not be evaluated and thus remains an item for future research. At least from a conceptual point of view, from the perspective of ecological classification of forests, it would stand to reason that a classification based on multi-temporal spectral data should be superior to one based on the traditional single-date spectral classification. As such, a classification based on multi-temporal spectral data would have (i) include the spectral information used in traditional supervised classifications, but (ii) also possess temporal data with which to distinguish forests based on temporal variation such as phenology.

III. Study implications

Spatial heterogeneity of tropical forests

One effect of one of the more significant recent studies (Morton et al. 2014) on the impacts of BRDF on MODIS time-series data was that it caused a re-examination of previous studies which had not considered the issue of BRDF in their analytical and experimental designs. In a similar vein, one of the co-authors followed up with a study on BRDF effects in non-time-series Landsat data (Nagol et al. 2015). Both studies does highlighted the importance of considering BRDF's impacts both spatially and temporally and provided some grounding of this thesis' overall approach. Specifically on the issue of how BRDF affects the spatial aspects of spectral data, an important consideration is the link between the spatial heterogeneity of forests and the spatial heterogeneity of canopy spectral response, as estimated by satellite sensors.

Those sensors, for instance, collect data on canopy spectral response, which in the case of French Guiana, shows undulating patterns across the territory's landscape. A number of previous studies have essentially ignored that the sensors on the Landsat satellites are not exclusively nadir-viewing and have not considered distortions in reflectance across the scenes imaged. However, the various sensors on the Landsat satellites have fields of view on the order of 15 degrees (Nagol et al. 2015). The first part of Chapter 1 has characterized the distortions in the Landsat reflectance estimates using data collected over French Guiana. The second part of Chapter 1 likewise took that distorted reflectance data and demonstrated that it yields sub-par estimates of forest type distributions.

The broader implication of Chapter 1 is thus that there are (i) distortions in Landsat reflectance data, if not corrected for BRDF by researchers using that data, and (ii) those distortions will necessarily impact derived products. And certainly, such distortions will not only affect French Guiana, such distortions will affect all tropical regions. In other words, thirty-plus years' worth of remote sensing-based studies of forest types, land cover, and vegetation types have likely been impacted to some degree by BRDF and may thus warrant revisiting. The BRDF-driven reflectance distortions have, in fact, been reported in previous studies (Danaher 2002; Toivonen et al. 2006; Hansen et al. 2008; Potapov et al. 2012; Muro et al. 2016). The first part of Chapter 2, however, not only documents such distortions, but provides a quantitative characterization of the impact of BRDF on forest canopy reflectance. Further, the second part

of Chapter 1 provides a basic methodology for correcting such effects using other data sources such as MODIS.

Tropical forests and temporal variation

For the better part of three years, since the publication of one influential study in *Nature* (Morton et al. 2014), in response to earlier studies (Huete et al. 2006; Saleska et al. 2007), there has been a debate ongoing regarding the extent to which satellite-derived vegetation indices can be properly applied to monitoring tropical forest phenology, particularly in the tropical evergreen forests of the greater Amazon. One side – Huete, Saleska, and colleagues – essentially wagers that vegetation indices provide sound evidence of phenological variation in Amazonian forests, consistent with greening in the dry season, while the other side – Morton, Samanta, and colleagues – argues it is merely an instrumental artefact due to BRDF effects on the vegetation index data used. While the findings presented in Chapter 2 were not meant to favour one side or the other, their findings ultimately suggest that the forests in the Guiana Shield (specifically in French Guiana) do indeed green-up during the dry season.

Great effort was taken to ensure that BRDF-corrected vegetation index data was used to derive such a finding, and statistical analyses and complex radiative transfer modelling simulations were done to verify whether the observed variation in the corrected indices were indeed merely the result of bi-directional effects. The conclusion was that the observed intra-annual variation in the vegetation indices is more correlated with environmental factors (e.g. intra-annual variation in incident solar radiation) than with atmospheric factors (e.g. cloud cover or aerosols) or bi-directional effects caused by solar direction variation.

Furthermore, these findings are parallel to other findings from field studies in Brazil which used phenological camera (phenocam) data to show that Amazonian forests are experiencing peak greenness during the dry season months (Wu et al. 2016; Lopes et al. 2016). However, it is acknowledged that simply because forests at plots in the Brazilian Amazon are greening up in the dry season is not evidence enough that forests in French Guiana must be undergoing similar processes. Nevertheless, such field data tend to provide credence to this thesis' findings. The radiative transfer modelling at the plot level essentially concludes that the vegetation index variation observed by satellite sensors like MODIS (parallel to the variation also indicated by VEGETATION) does not match what would be expected based solely on variation in solar direction. Therefore, the plot-level modelling indicates that the variation observed by MODIS and VEGETATION are not caused by BRDF. Further, the regional-level statistical analyses of the time-series data from the Guianas, central Africa, and Borneo demonstrate that the three regions' vegetation index variation are quite different, and driven by / correlated with different factors. This is also supported by another cross-continental study on climate seasonality and carbon assimilation (Wagner et al. 2016). This suggests that the observed variation is not an instrumental artefact (i.e. BRDF). The last part of Chapter 2 essentially reproduces the findings of the earlier study done by Pennec et al. 2011 which had originally posited that French Guiana's forests displayed phenological variation. However, there were doubts since the data used in that study were not corrected for BRDF. But when data corrected for BRDF effects are used, they still show seasonality, and indicate that different types of forests peak in their greenness during different months, suggesting that the variation is not due to BRDF.

Ultimately, the findings of Chapter 2 provide evidence for seasonally occurring changes in forest structure (i.e. leaf exchange, litterfall) and / or changes in leaf optical properties (e.g. changes in leaf reflectance due to the emergence of new leaves, as suggested by D. Sabatier). While these studies do not outright indicate what is indeed driving the seasonal changes in the vegetation indices, other, unpublished data likewise support the idea of changes in forest structure and leaf optical properties. For instance, analysis of transmittance estimates derived from LiDAR overflights over Paracou in French Guiana from September 2011, September 2013, and October 2015 indicate that the plant area index (PAI) of Paracou is higher in October than in September, indicating that the forest there is “leafing up” at the very height of the dry season. Furthermore, unpublished data collected at the Nouragues field site in French Guiana by Jean-Baptiste Feret (personal communication) also suggests that in terms of leaf demographics, the new leaves which are being produced in the dry season (Sabatier 1985; Sabatier and Puig 1986) do exhibit higher near-infrared reflectance than older leaves. While this would make for an interesting radiative transfer study to confirm such, it would suggest that vegetation indices would indeed peak in the dry season due to leaf flush.

IV. Limitations

Of note are the limitations of this thesis as regards aspects of the temporal analysis, and the spatio-temporal analysis. The limitations, however, mainly concern data not available at the time of this study, but which may yet be available for future follow-on work.

Regarding the former limitation, it is noted that this thesis’ component temporal studies did not benefit from field observations to ground the study findings. This, in turn, was due to the overall lack of time-series of phenological observations in tropical regions. As such, while the findings of the temporal analyses were compelling, they could have been even more compelling had there been readily available field measurements to complement the satellite data. For instance, two recent studies of note (Wu et al. 2016; Lopes et al. 2016) complemented their satellite-based analyses with analyses of data from phenological cameras (phenocams) to draw strong conclusions about the reality of dry season leaf flush in Amazonian forests. While such data was not available for French Guiana, it is expected that in the future, similar types of data – or data collected from more regular monitoring of phenology (extending on the work of Wagner et al. 2013) will be able to complement the analyses done. However, it should also be noted that the intensive radiative transfer modelling simulations engaged was also conducted as a means of supplementing the analyses of satellite data. While these cannot replace field data, it is anticipated that the development of more advanced hypotheses will drive further radiative transfer modelling to better understand the processes occurring in French Guiana’s forests.

In addition to the temporal analyses, another area which was limited by the lack of data corresponded to the spatio-temporal analysis presented in Chapter 3. That chapter sought to build on the approach proposed by a previous study on the remote sensing of plant functional types (Ustin and Gamon 2010) which advocated using a range of datasets to examine the issue of functional types, including very high spatial resolution (VHSR) data on forest structure, hyperspectral data on canopy biochemistry and physiology, and high frequency data on

phenology. Ultimately, as was discovered by the authors of another application of that approach, albeit in temperate forests (Huesca et al. 2015), the data for fully implementing Ustin & Gamon's proposal was simply not there. As such, while VHSR data on forest structure and hyperspectral data on biochemistry would have been extremely useful in terms of the forest typology work, this study had to rely on the best available data, which did correspond to 12 years' worth of monthly canopy reflectance derivatives (i.e. vegetation indices) from MODIS. It is likewise anticipated that future follow-up to this research may benefit from data not currently available for improved discrimination of forest types.

V. Perspectives on future research

As this research focused on particular research questions, the findings of the studies conducted likewise inspired new questions, which will hopefully set the context for future studies, not just of French Guiana's tropical evergreen forests, but also of tropical forests in general.

Spatial variation

Where it was demonstrated that Landsat-5 and Landsat-7 data are, as one would expect, subject to bi-directional effects which results in anisotropic reflectance across satellite sensor scanning tracks, it remains to be seen how such bi-directional effects affect other satellite sensors. While one potential avenue of research would be a broader characterization of how BRDF affects reflectance data across seasons, recent happenings also suggest other avenues for future research related to spatial variation. For instance, it has been announced that the European Space Agency (ESA) and NASA are planning to, in the near-term, release blended reflectance estimates generated from both the US' Landsat-8 and ESA's Sentinel-2, and already corrected for bi-directional effects. As this thesis' study of forest types was based on reflectance data corrected for BRDF using a new method developed during the course of this research, it would be expected that reflectance estimates generated from the proposed blended Landsat-8 / Sentinel-2 data would be different from those generated for this research. It would thus be useful, when such reflectance estimates become available, to repeat the forest type mapping using such data.

It is possible that the findings of the second part of the first main chapter may have been influenced partly by the quality of the inputs used (e.g. spatial noise introduced by the reliance on Landsat-7 reflectance estimates which were filled for gaps resulting from its sensor's 2003 Scanline Corrector malfunction) (Lillesand et al. 2007). It is thus expected that data from sensors not so affected, or with higher geometric accuracy (e.g. Landsat-8, Sentinel-2) might produce superior reflectance estimates. Additionally, it should be noted that the Landsat-5 and Landsat-7 data used in the study were collected by scanning, whisk broom sensors (Thematic Mapper and the Enhanced Thematic Mapper+, respectively), and it may be that the reflectance estimates derived from the push broom-based sensors on Landsat-8 and Sentinel-2 may provide higher quality reflectance estimates (Lillesand et al. 2007).

Temporal variation

One way in which the issue of dry season green-up in French Guiana could be conclusively determined would be the collection of multi-temporal data on transmittance, via the use of LiDAR. Due to the high acquisition costs for aerial LiDAR, perhaps the collection of terrestrial LiDAR, on a ~monthly basis over a year, would be sufficient. This would allow for characterizing how the structure of the forests at sites like Paracou, for instance, change over time and would complement the data already collected for such sites from aerial (2009, 2011, 2013, 2015, 2016) and terrestrial LiDAR (2014, 2015, 2016). It would help to put to rest the issue of whether or not French Guiana's forests are indeed greening up in the dry season. The radiative transfer modelling study in the temporal variation chapter of this thesis, for instance, was based on an assumption that forest structure (LiDAR-derived) is not changing significantly from month to month, but actually having multi-temporal LiDAR data would allow for more realistic modelling. Furthermore, it would be extremely simple to derive estimates of plant area index from such data using the AMAPvox platform (Vincent et al. 2015).

However, as the LiDAR data principally provides information on forest structure, it might not necessarily be suited to study of the variation in canopy biochemistry of French Guiana's forests. In the course of this study, satellite-derived hyperspectral data which could theoretically aid in such characterization of canopy biochemistry were collected over sites like Nouragues and Paracou, but these data were subject to the problem which typically affects tropical forest territories – high cloud cover, particularly during the wet season. As such, it was not possible to study variations in canopy biochemistry with such data. Further, the hyperspectral reflectance data collected by the only functioning spaceborne hyperspectral scanner (EO-1 Hyperion) are collected at the spatial level of detail of 0.09 hectares (30m x 30m), which would necessarily average the spectral responses from multiple canopy trees. It would be preferable, in future studies, to be able to characterize canopy biochemistry using finer resolution aerial hyperspectral data, such as was only recently collected over Nouragues and Paracou in September 2016. Nevertheless, monitoring the intra-annual changes in canopy biochemistry would require collecting such aerial hyperspectral data at least on a monthly basis. Due to the high costs of collecting such data with traditional manned aircraft, possibly such work could be done using an unmanned aerial vehicle (UAV), i.e. a drone. Such work would also facilitate understanding phenological variation of French Guiana's forests.

In fact, the work already being done by this project's two main host institutions go in those directions. For instance, the Forest Biometry and Forest Systems Analysis lab of the Technische Universität Dresden (TUD) is exploring the use of drone data for monitoring temperate forest growth (J. Vogt, personal communication). On the other hand, researchers from IRD / AMAP are using drones with multispectral sensors to study gap dynamics and canopy structure in Cameroon, and plan to add additional sensors (hyperspectral and LiDAR) to measure forest structure and monitor the dynamics of canopy biochemistry (N. Barbier, personal communication).

Spatio-temporal analysis

The third chapter of this thesis (on spatio-temporal analysis) was not exhaustive in exploring how multi-temporal spectral data could be used for characterizing forest types based on their spectral-temporal ‘signatures.’ Further research is recommended, especially as the time-series of observations expands. While it is not expected that a larger time-series will necessarily fill in gaps caused by wet season cloud cover, there are alternative, new sources of data which are expected to enhance the understanding of spatio-temporal dynamics.

As an example, in early November 2016, the National Oceanographic and Atmospheric Administration (NOAA) of the U.S. Government plans to launch the advanced GOES-R meteorological satellite (Shao et al. 2014). GOES-R differs from prior meteorological satellites in that one of its imagers will be the Advanced Baseline Imager (ABI), which is a ‘legacy sensor’ to MODIS (Schmit et al. 2008). Combined with the high temporal resolution at which GOES-R will be imaging the Americas (once every five minutes on standard mode), will allow for something that has not been possible even with twin MODIS sensors: diurnal characterization of vegetation (Schmit et al. 2005; Schmit et al. 2008; Hillger et al. 2011). Where, for example, MODIS can only provide two snapshots of EVI or NDVI per day, GOES-R’s ABI will be able to provide such estimates throughout the course of the entire day, cloud cover notwithstanding. This will not only allow for eventually imaging areas which are missed by MODIS due to cloud cover, this will also allow for better characterization of how BRDF related to changing sun heights and azimuths affects vegetation index estimates. However, one major drawback of the ABI is that its data will have less spatial detail than either MODIS or the VEGETATION sensor currently on Proba-V (De Vos et al. 2009; Sterckx et al. 2014). Another drawback may be the processing limitations related to the extremely large volume of data that will be collected by GOES-R (Schmit et al. 2008).

VI. Overall scientific contribution

In terms of this PhD thesis’ overall contribution to science, this project has addressed specific research gaps related to the diversity and spatio-temporal variation of tropical forests. Regarding the distribution of forest types, this research has contributed to the development of a new map of ecologically consistent forest types of French Guiana. While other maps of forest types of French Guiana already exist (Girou 2001; Gond et al. 2011; Guitet et al. 2015), this research project has taken another approach to forest types, and also discriminated some forest types not identified by prior efforts (e.g. liana-covered forests, secondary forests, and *Parinari campestris*-dominated forests). With regard to the issue of temporal variation, vis-à-vis phenology, this project’s main contribution has been to weigh in on a current debate and to demonstrate that, at least in the case of the Guianas and central Africa, the variation in satellite-derived vegetation indices is not an artefact caused by bi-directional reflectance distribution function (BRDF) or atmospheric effects. Indeed, the analysis indicates that the observed variation in vegetation indices – for both the Guiana Shield and central Africa – is closely linked to seasonal climatic variation. Furthermore, the different patterns observed for each region is likely due to differences in species composition between the regions.

While Chapters 1 and 2 focused on research gaps related respectively to spatial and temporal variation of forests, Chapter 3 built on the findings of those chapters to chart a new research direction. As such, this thesis has explored a new direction in the area of forest type mapping. This thesis has gone beyond traditional approaches to remote sensing-based classifications of forest types which only consider the spatial heterogeneity of forest types based on canopy reflectance images acquired at single points in time. This thesis has, through analysis of time-series of spectral data and radiative transfer modelling, built a case that when combined, spatial and temporal forest canopy reflectance estimates can yield ecologically meaningful insights into forest typology (also provided that atmospheric and instrumental artefacts are accounted for). The approach piloted in this thesis has also thus grounded a study design proposed in an earlier study (Ustin and Gamon 2010), and explored for the tropical forests of French Guiana an approach already piloted for temperate forests (Huesca et al. 2015). It has likewise built on the approaches of previous studies (Bradley et al. 2011; Viennois et al. 2013; Huesca et al. 2015) and tried approaches distinct from earlier studies of forest typology in French Guiana (Girou 2001; Gond et al. 2011; Guitet et al. 2015). It also follows that there are multiple avenues for future research which this thesis has laid the groundwork for. These include new research questions related to the linked issues of the spatial and temporal variation of tropical forests.

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Résumé: Contribution à la cartographie des types forestiers de Guyane française à partir de l'analyse des patrons spatio-temporels de réflectance obtenus par télédétection satellitaire

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Mots clés : écologie forestière, forêts tropicales humides, évolution temporelle, phénologie, modélisation du transfert radiatif, Landsat, MODIS, SPOT VÉGÉTATION

I. Introduction

Les forêts tropicales fournissent des services écosystémiques globaux mais sont de plus en plus menacées par la pression anthropique. Il en résulte un besoin pressant de mieux caractériser la diversité biologique (taxonomique et fonctionnelle) de ces milieux. La connaissance accumulée à travers les inventaires botaniques et les études écologiques à l'échelle stationnelle peut être utilement complétée par une approche spatiale intégrative à l'échelle du paysage ou de la région. Cette thèse explore certains aspects de l'hétérogénéité spatiale et temporelle des canopées forestières de Guyane (**Figure 1**) telle que caractérisée par différents capteurs satellitaires en vue de proposer une typologie forestière écologiquement pertinente. Dans ce cas, la Guyane sert d'étude de cas pour d'autres forêts tropicales.

La première étape de ce travail a été d'identifier et de corriger certains artefacts instrumentaux dans les données de télédétection utilisées. L'anisotropie de la réflectivité des couverts forestiers affecte les mesures spectrales. Cette anisotropie est caractérisée par la fonction de distribution de réflectivité directionnelle dont l'acronyme en anglais est la BRDF (*'bi-directional reflectance distribution function'*). La BRDF des couverts forestiers est complexe et dépend notamment de la rugosité de la canopée, des propriétés optiques des feuilles et de leur orientation. Le second chapitre traite de l'importance des effets de BRDF dans les images multispectrales utilisées et des conséquences de leur non prise en compte sur les classifications ultérieures. L'analyse des données mensuelles de réflectance corrigées des effets de BRDF suggère que des changements saisonniers affectant la structure ou les propriétés spectrales intrinsèques de la canopée sont à l'œuvre.

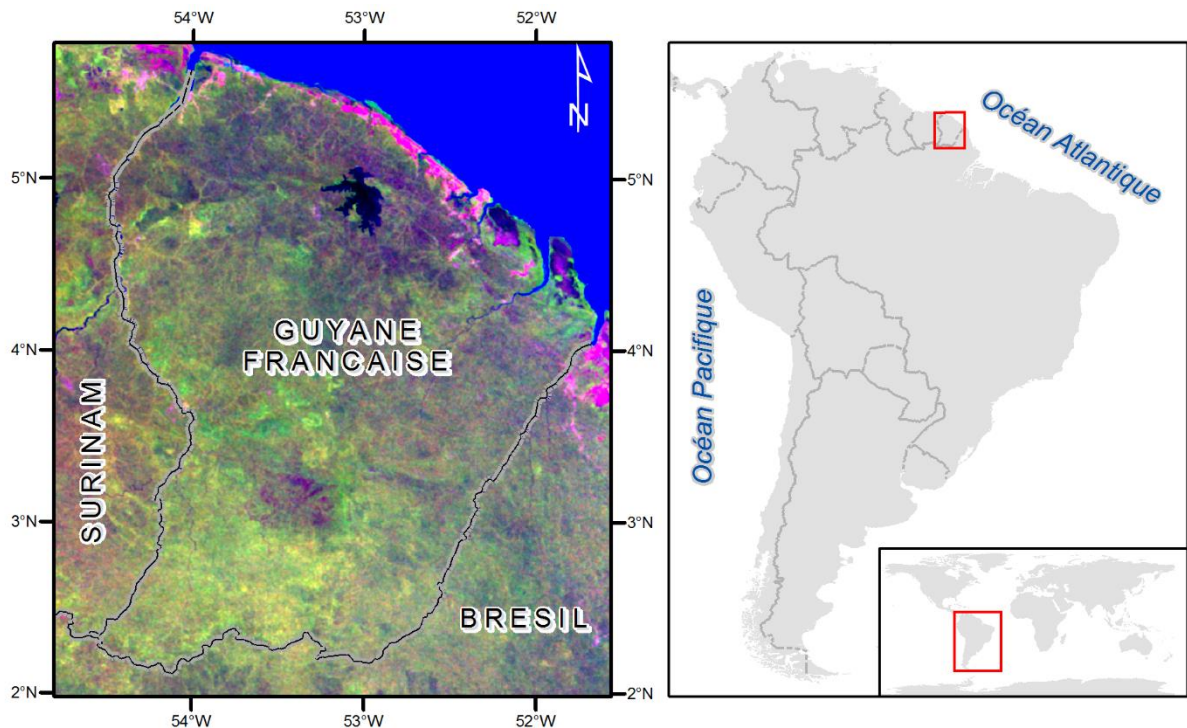


Figure 1 : Moyenne de réflectance de la Guyane pour septembre, dérivée de MODIS MCD43A4 (gauche); emplacement de la Guyane française en Amérique du Sud (droite)

Bien que la BRDF soit un phénomène physique fondamental, les angles d'acquisition des images par un satellite sont variables et créent des artefacts d'observation qui peuvent conduire à des conclusions erronées sur les changements réels de la végétation. Pour examiner les questions de variation spatiale et temporelle des forêts tropicales tout en prenant en compte la BRDF, la présente recherche aborde les questions suivantes :

Axe 1 : Évaluation de la variabilité spatiale de la réponse spectrale des forêts tropicales

1. Comment les effets bidirectionnels affectent-ils la variation spatiale de la réponse spectrale des forêts tropicales et comment affectent-ils la variation spatiale des distributions estimées des types forestiers ?
2. Les distributions spatiales estimées des types forestiers sont-elles robustes vis-à-vis de la saison d'acquisition des images ?

Axe 2 : Évaluation de la variabilité temporelle de la réponse spectrale des forêts tropicales

3. Dans quelle mesure la variation saisonnière observée des indices de végétation (VIs) des forêts tropicales correspond-elle à la variation saisonnière du climat ou aux artefacts instrumentaux ou atmosphériques ?

4. Dans quelle mesure la variation du VI modélisée en fonction seulement du changement d'élevation solaire est-elle en corrélation avec les observations de télédétection ?

5. Si les variations saisonnières des VI ne sont pas un artefact, que signifient les données corrigées en termes de modèles saisonniers pour les forêts tropicales ?

Axe 3 : Examen des patrons combinés de variation spatio-temporelle pour identifier les types forestiers

6. Dans quelle mesure l'utilisation des données spatio-temporelles permet-elle une caractérisation cohérente de la distribution spatiale des types forestiers ?

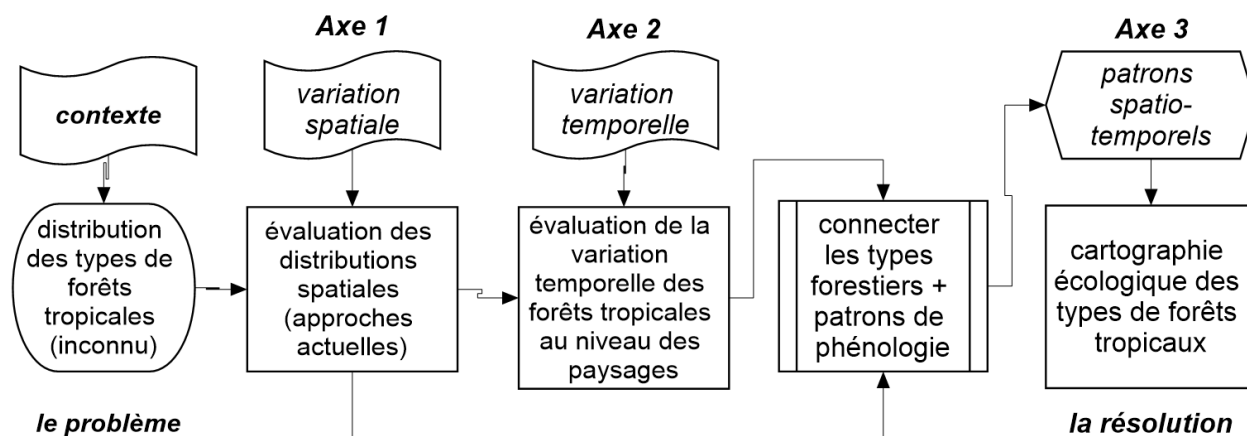


Figure 2 : Liens entre chapitres

II. Méthodologie

Différentes méthodes ont été nécessaires pour aborder les questions de recherche de cette thèse. Pour l'évaluation des schémas de variation spatiale des forêts de la Guyane française, les analyses se sont basées sur la classification des données Landsat et MODIS. Cette caractérisation a également été aidée par l'analyse de la façon dont les effets bidirectionnels affectent les estimations de la réflectance de la canopée. En complément de ces analyses, les données chronologiques de MODIS et SPOT VEGETATION ont été analysées par des méthodes statistiques pour caractériser les variations temporelles saisonnières au niveau du paysage. Contrairement à la caractérisation des variations spatiales, la caractérisation des variations temporelles a été complétée par des analyses des déterminants environnementaux potentiels de cette variation, ainsi que des analyses de l'influence des artefacts atmosphériques et instrumentaux (bi-directionnels). L'analyse des séries chronologiques a également été complétée par des simulations de transfert radiatif qui ont permis de comprendre quels processus peuvent entraîner une variation temporelle de la réponse spectrale

des canopées forestières. Enfin, lorsque l'on a recueilli des informations sur les modèles spatiaux et temporels, on a analysé une grande archive de données spatiales et temporelles en utilisant des techniques de décomposition en séries chronologiques pour caractériser les types de forêts.

Les trois sections suivantes décrivent plus en détail les méthodes utilisées pour chaque axe :

Axe 1 : Évaluation de la variabilité spatiale de la réponse spectrale des forêts tropicales

En vue de l'applicabilité des données Landsat à la cartographie des types de forêts en Guyane basée sur les différences subtiles de réflectance entre types de forêts, des analyses ont été effectuées pour déterminer dans quelle mesure les estimations de la réflectance de surface Landsat sont influencées par la BRDF. Les estimations de réflectance de surface ont été obtenues à partir de données Landsat brutes et la variation de la réflectance le long de la piste de balayage Landsat a été examinée, ainsi que dans quelle mesure les estimations de réflectance Landsat différaient des données de réflectance MODIS déjà corrigées pour les effets de BRDF. Ces données - non corrigées et corrigées pour la BRDF - ont été utilisées avec des données de terrain pour générer des cartes de type de forêt en utilisant des algorithmes de classification supervisée. Les résultats des deux classifications ont ensuite été comparés pour évaluer la cohérence entre les cartes des types forestiers obtenues. De plus, des mesures de similarité spectrale ont été générées pour évaluer la qualité des cartes de type forestiers, comme exercice de validation.

De plus, en complément à l'évaluation de la façon dont les effets de BRDF influent sur les estimations de la répartition des types forestiers, des analyses supplémentaires se sont concentrées sur la façon dont les estimations de la distribution des types forestiers varient temporairement dans les données déjà corrigées de la BRDF. Ceci est lié à la deuxième question de recherche, qui a porté sur la façon dont les estimations des distributions spatiales des types de forêts tropicales changent selon la saison. Dans l'ensemble, les méthodes ont consisté à (i) extraire des données de réflectance pour la classification de la couverture forestière, (ii) cartographier des types forestiers, (iii) évaluer la séparabilité des types forestiers.

Axe 2 : Évaluation de la variabilité temporelle de la réponses spectrale des forêts tropicales

Pour examiner comment la BRDF aurait pu influencer la variation temporelle des indices de végétation, on a émis l'hypothèse que lorsque les zones situées à la même latitude sont sous des «régimes» d'élévation solaire similaires, si la variation observée des VIs est effectivement influencée par la BRDF, la même latitude devrait afficher des variations de VI identiques. Cette hypothèse a été testée en comparant les données VI

des forêts tropicales sempervirentes dans trois zones au nord de l'équateur (les Guyanes, l'Afrique centrale et le nord de Bornéo) – **Figure 3**.

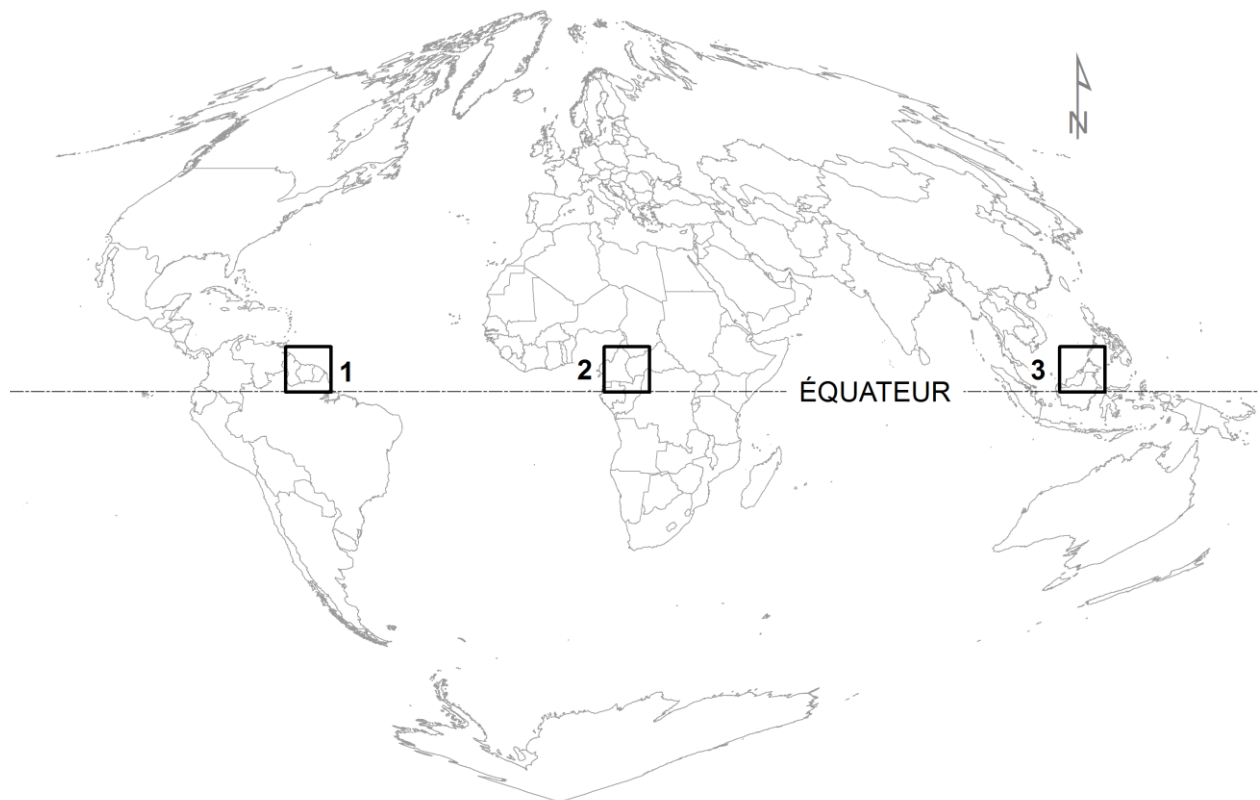


Figure 3 : Localisation des zones d'étude pour l'évaluation régionale de la variation du VI (1: Plateau des Guyanes, 2: Afrique centrale, 3: Bornéo nord).

Deuxièmement, pour revenir sur les résultats d'études satellitaires antérieures sur la variation phénologique des forêts amazoniennes, l'étude actuelle a porté sur la variation des indices de végétation de la Guyane française. Plus précisément, 12 années de données VI traitées pour des effets bidirectionnels ont été extraites des archives de 2 capteurs satellitaires: l'instrument SPOT VEGETATION et MODIS (the MODerate resolution Imaging Spectroradiometer).

Enfin, pour étudier les effets de BRDF au niveau des parcelles de terrain, on a utilisé le modèle de transfert radiatif anisotrope discret (DART) avec les données LiDAR aériennes pour simuler la réflectance du couvert et dériver les estimations de l'indice de végétation amélioré (EVI) pour des forêts tropicales de structure variable dans trois sites à travers la Guyane française. La réflectance et l'EVI ont été simulées sur des échelles de temps de plusieurs mois ainsi que sur des jours choisis, afin d'examiner comment la variation de l'élévation solaire affecte les estimations de la réponse spectrale de la végétation en l'absence de variation phénologique.

Axe 3 : Examen des patrons combinés de variation spatio-temporelle pour identifier les types forestiers

Le troisième axe a exploré dans quelle mesure les données spatiales et temporelles pouvaient contribuer à une cartographie écologiquement pertinente des types de forêts tropicales, en se concentrant sur l'exemple de la Guyane française. Les données mensuelles de l'indice de végétation améliorée (EVI) dérivé de MODIS pour la Guyane française pour la période 2002-2014 ont été filtrées spatialement puis soumises à une analyse temporelle qui a permis d'extraire les fluctuations saisonnières de la variation spatiale EVI des archives sur 12 ans. Par une approche de classification non supervisée, les cinq principaux types de forêts ont été cartographiés, sur la base des modèles dominants de variation spatiale et temporelle.

III. Résultats

Axe 1 : Variation spatiale des forêts de Guyane

Le premier chapitre de cette thèse examine comment la BRDF affecte la réflectance de la canopée des forêts en Guyane et comment le fait de ne pas corriger la BRDF affecte les classifications spectrales de ces forêts. Une carte préliminaire des types de forêts de la Guyane française a été générée à partir des données Landsat corrigées pour la BRDF (**Figure 4**). Cependant, lorsque l'on examine les données de réflectance mensuelles corrigées, elles suggèrent des changements saisonniers dans la structure forestière ou les propriétés spectrales des forêts de la Guyane française. Ce qui a été démontré, c'est que de petites différences dans les paramètres d'acquisition du capteur peuvent entraîner une distorsion de la réflectance spectrale des forêts tellement grande que la même zone donnera des estimations extrêmement différentes de la distribution des types forestiers (**Figure 5**). Il est également très illustratif que deux mosaïques assemblées à partir des mêmes ensembles de données Landsat en entrée, mais avec un traitement différent (c'est-à-dire la correction ou non de la BRDF) donneraient des cartes qui sont différentes à plus de 70%.

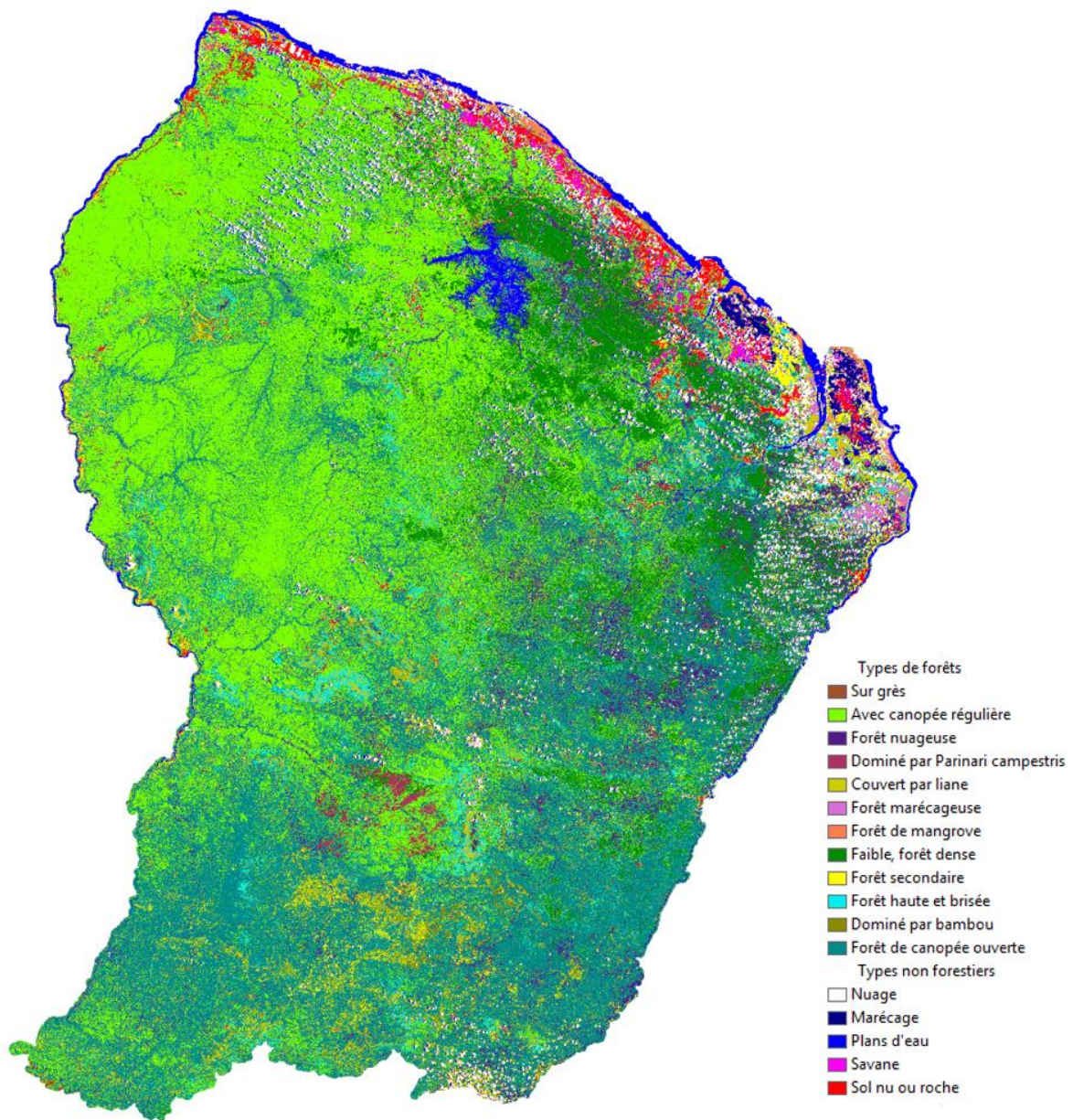


Figure 4 : Carte des types forestiers, basée sur les données Landsat corrigées pour la BRDF

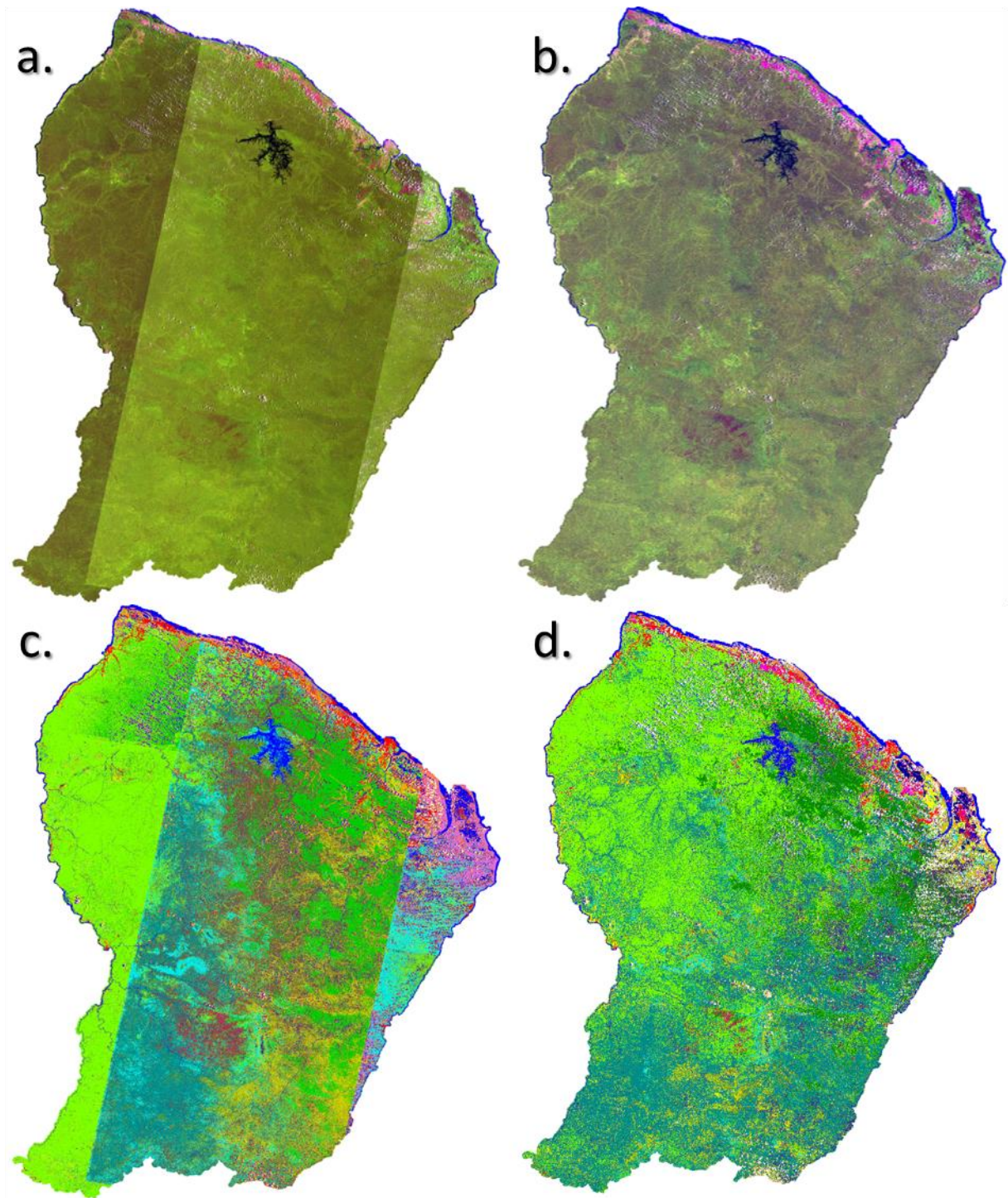


Figure 5 : Estimations de réflectance dérivées de Landsat: non corrigées pour la BRDF (en haut à gauche) et corrigées pour la BRDF (en haut à droite); Classifications des types de forestiers: générées à partir des données de réflectance non corrigées pour la BRDF (en bas à gauche) et générées à partir des données corrigées pour la BRDF (en bas à droite). (Note: les cartes des types forestiers ont la même légende que la **Figure 4**.)

Contrairement aux **Figures 4** et **5**, la **Figure 6** a également démontré que non seulement les estimations des types forestiers dépendent des corrections de la BRDF, mais que les classifications diffèrent d'un mois à l'autre, probablement en raison de différences phénologiques. Dans le cas de la figure 6, les données d'entrée ont été corrigées pour la BRDF.

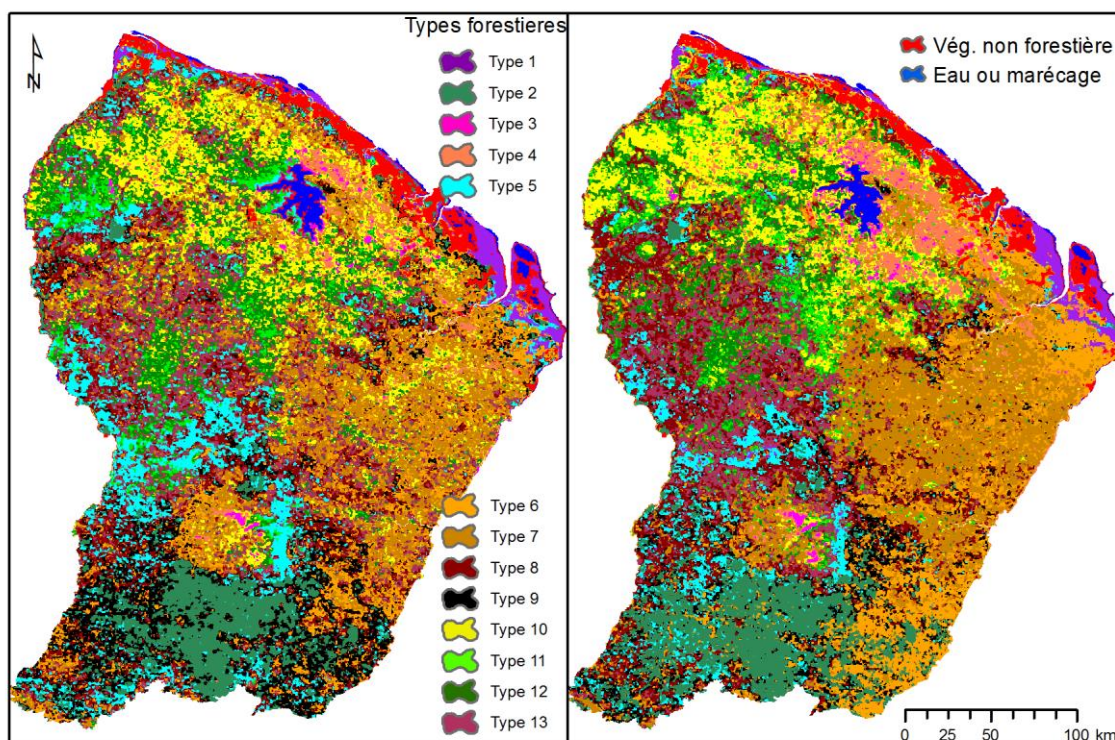


Figure 6 : Cartes des types forestiers, basées sur la réflectance moyenne d'août (à gauche) et de septembre (à droite).

Axe 2 : Variation temporelle des forêts de Guyane

Le second chapitre de cette thèse examine les effets temporels de BRDF et a utilisé des comparaisons inter-régionales et des modèles de transfert radiatif au niveau pour chercher à comprendre les moteurs de la variation mensuelle de la réflectance du couvert forestier. Pour ce dernier cas, le modèle DART (Discrete Anisotropic Radiative Transfer) a été utilisé avec des observations au scanner laser aérien (ALS) sur différentes structures forestières, ce qui indique que la variation observée de la réflectance (et des dérivés connus sous le nom d'indices de végétation) suit la course du soleil (**Figure 7**).

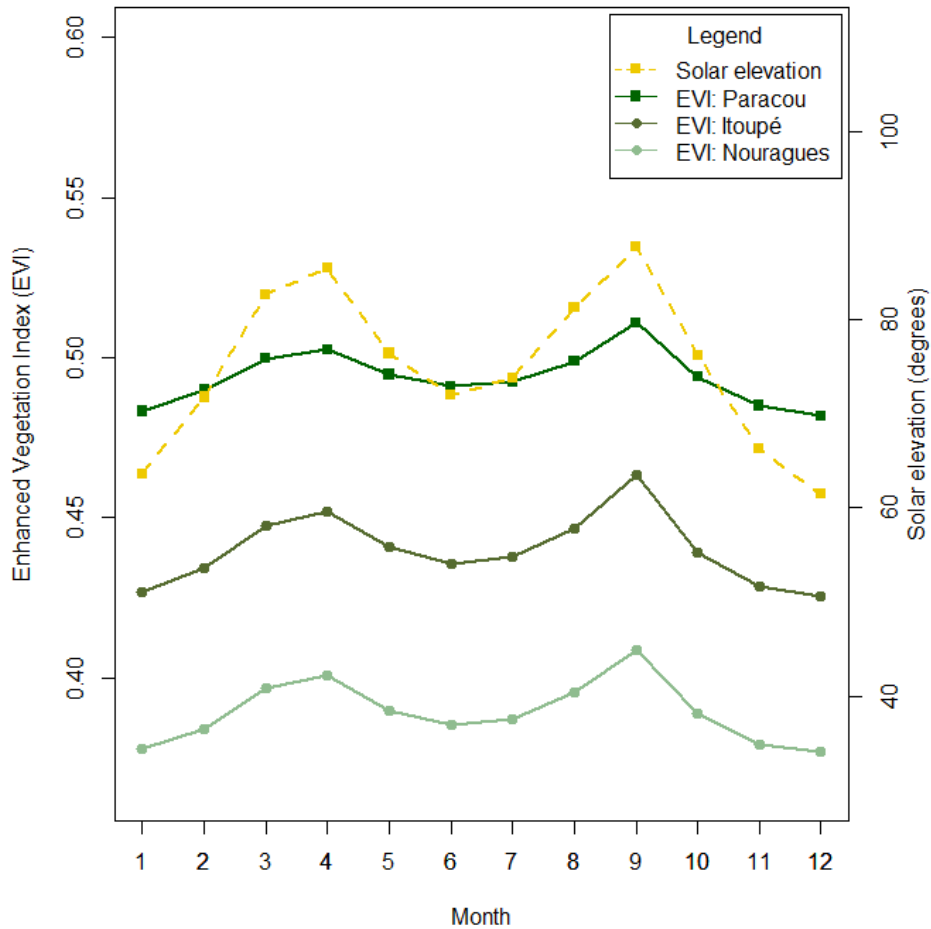


Figure 7 : Variation mensuelle de l'altitude solaire au midi solaire et variation modélisée de l'EVI aux trois sites d'étude (sur la base d'une LAD sphérique).

À l'échelle régionale, il a également été démontré que les forêts du Bouclier guyanais montraient une variation temporelle distincte des forêts d'Afrique centrale ou du nord de Bornéo, pourtant toutes situées juste au-dessus de l'équateur. Si la variation temporelle observée dans les indices de végétation était le résultat d'effets de BRDF, on aurait pu s'attendre à ce que les forêts dans les trois zones aient des modèles de variation semblables, ce qu'ils n'ont pas (**Figure 8**). D'autres analyses ont montré que les forêts d'Afrique centrale semblaient avoir une phénologie synchronisée avec les précipitations, alors que les forêts des Guyanes semblaient synchronisées avec la disponibilité du rayonnement solaire.

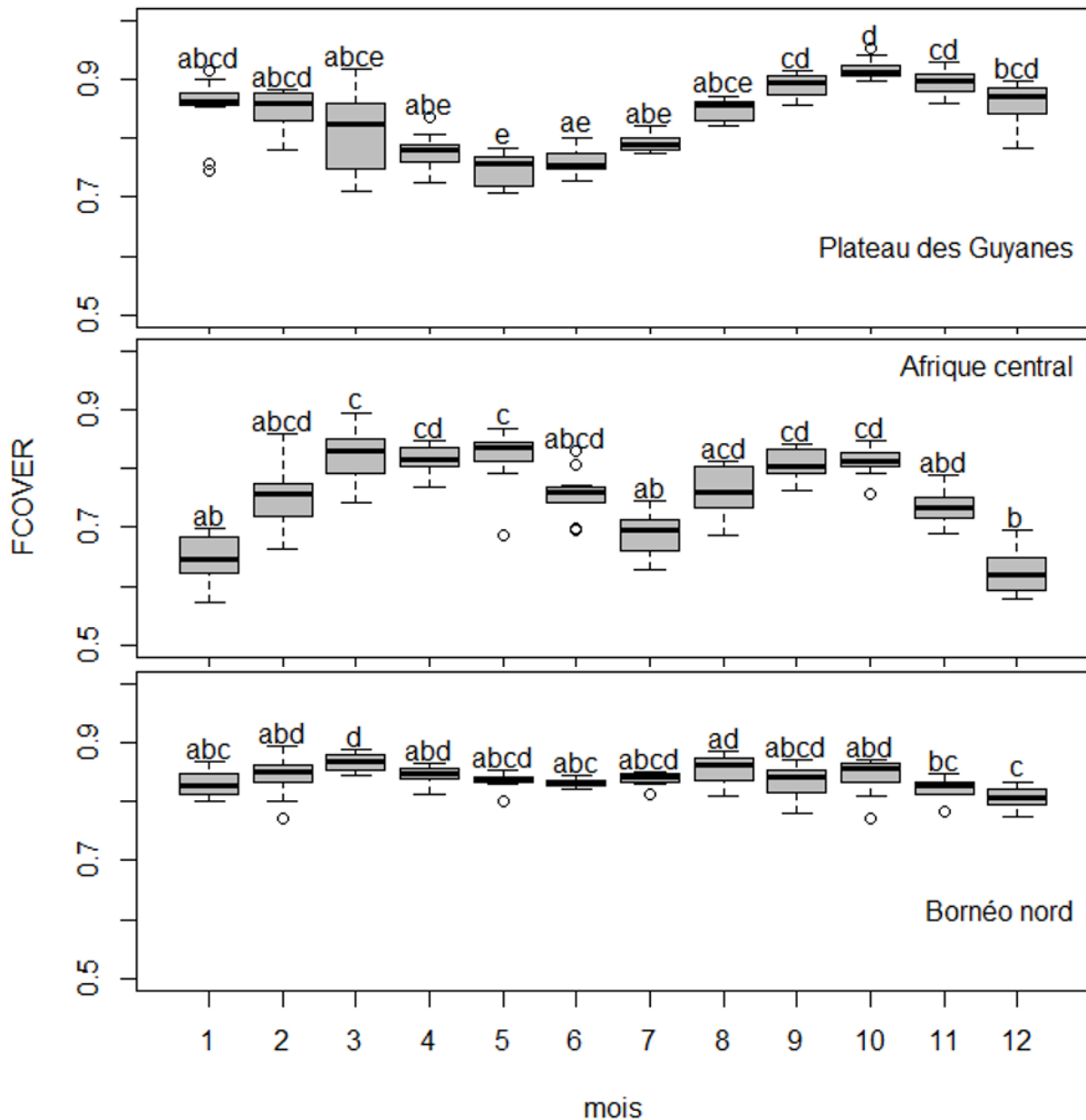


Figure 8 : Variation mensuelle de l'indice de végétation FCOVER dans 3 régions tropicales.

Axe 3 : Patterns spatio-temporels de variation de la réponse spectrale des forêts tropicales

Une des principales constatations du troisième chapitre est que les différents types de forêts en Guyane possèdent des modèles de variation temporelle distincts, ce qui suggère que des types forestiers peuvent être discriminés sur la base de leurs «signatures temporelles» respectives (**Figure 9**). Cela a été exploité dans le troisième chapitre de la thèse, qui classe les forêts de Guyane sur la base de leurs schémas combinés de réflectance spatio-temporelle et, ce faisant, présente une nouvelle façon de traiter la typologie forestière, basée sur des informations écologiquement

pertinentes. Il convient cependant de souligner que le travail présenté ici est préliminaire et que des améliorations futures peuvent être envisagées, en utilisant des données de résolution temporelle ou spatiales plus fines.

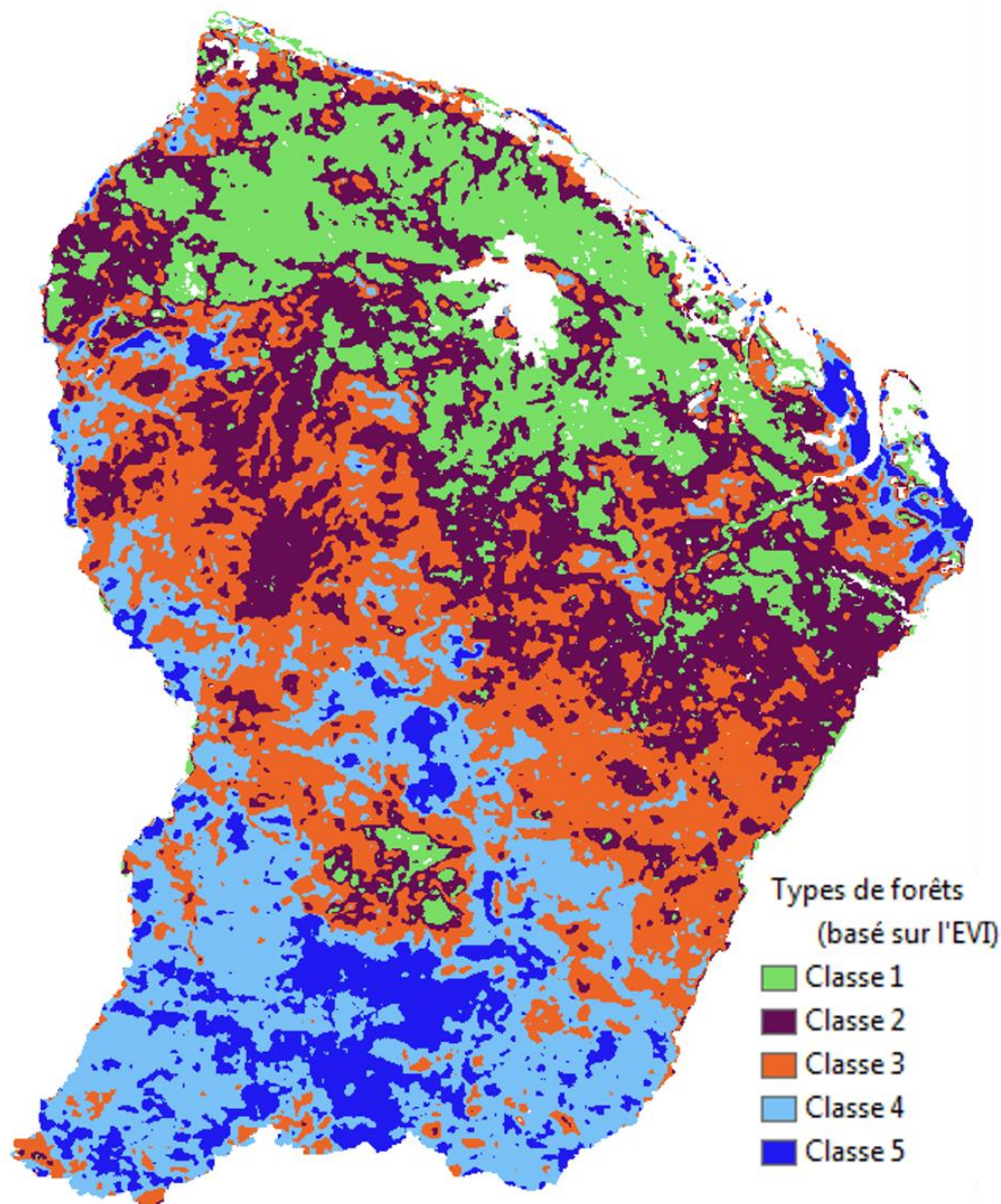


Figure 9 : Carte des types forestiers, basée sur l'analyse spatio-temporelle des données temporelles d'EVI

IV. Discussion

Pour tirer les conclusions de cette thèse, il est nécessaire de réexaminer les questions de recherche qui ont été posées au début de ce document. Ce projet de thèse a cherché à aborder six questions de recherche interdépendantes, présentées ci-dessous, avec des résumés des réponses apportées au cours de cette thèse.

i. Comment la BRDF affecte-t-elle la réponse spectrale des forêts et comment cela affecte-t-il les estimations des distributions des types forestiers ?

Le premier chapitre de cette thèse a démontré que la source de données de réflectance (Landsat) la plus couramment utilisée est en effet affectée par les effets bidirectionnels liés aux angles de balayage du capteur. Ainsi, les données de réflectance sur les parties occidentales des images Landsat sont plus éclairées que les données de réflectance des parties orientales des scènes Landsat. Le résultat est qu'il y a une anisotropie dans les estimations de la réflectance, et cela se traduit finalement par des estimations biaisées des types forestiers.

ii. Les estimations de la répartition des forêts changent-elles selon la saison ?

Il a été démontré que même lorsque les données sont corrigées pour les effets bidirectionnels mentionnés précédemment comme affectant les données Landsat, par exemple, les forêts sempervirentes de la Guyane française présentent une certaine saisonnalité dans leur réflectance. C'est ainsi que lorsque les types de forêts sont cartographiés en utilisant ces estimations de réflectance, les distributions de forêts semblent changer d'un mois à l'autre. Bien qu'il soit possible que les distributions des types de forêts cartographiées varient quelque peu d'un mois à l'autre en fonction de la variation de l'ombrage produite par les changements de direction solaire, des modifications substantielles de la réflectance du couvert auraient tendance à impliquer des changements dans la structure de la forêt et / ou des propriétés optiques des feuilles. Ceci est également lié aux résultats concernant la quatrième question de recherche, qui a examiné comment la variation de la direction solaire seule affecte la réflectance de la canopée.

iii. Dans quelle mesure la variation observée au niveau régional des indices de végétation correspond-elle à la variation climatique ou aux artefacts atmosphériques ou instrumentaux ?

Dans le prolongement de la troisième question de recherche, cette thèse a démontré que la variation au niveau régional des indices de végétation des forêts tropicales (en particulier celles du bouclier guyanais et en Afrique centrale) est plus corrélée avec les variations saisonnières de l'environnement qu'avec les conditions atmosphériques ou les artefacts instrumentaux. En outre, il a été démontré que la variation intra-annuelle des indices de végétation dans les deux régions est corrélée à différents facteurs. Ainsi, en Afrique centrale, la tendance des indices de végétation est fortement corrélée [positivement] avec les précipitations, alors que sur le Bouclier guyanais, la variation de l'indice de végétation est plus corrélée avec la variation du rayonnement solaire incident.

iv. Dans quelle mesure la variation temporelle des indices de végétation au niveau de la parcelle peut-elle être expliquée par la variation de la direction solaire ?

En ce qui concerne la quatrième question de recherche, cette thèse a démontré qu'au niveau des parcelles forestières, les variations observées avec les capteurs satellites ne peuvent pas être entièrement expliquées par les variations saisonnières des angles solaires. De plus, il a également été démontré que même les forêts dont la géométrie 3D et la densité du couvert sont très distinctes, ne montraient pas de tendances similaires dans la variation de l'indice de végétation comme supposer si l'élévation solaire était le principal moteur de la variation de l'indice de végétation. Comme cela n'est pas le cas, il est implicite que la variation de l'indice de végétation observée par les capteurs satellites doit être due à des changements optiques structuraux et / ou phénologiques.

v. À condition que la variation temporelle des indices de végétation ne soit pas due à des artefacts instrumentaux ou atmosphériques, comment cette variation varie-t-elle selon le type de forêt ?

En ce qui concerne la cinquième question de recherche, il a été démontré que lorsque les indices de végétation sont corrigés pour des effets bidirectionnels, à l'échelle de la Guyane française, ces indices présentent des tendances bien distinctes (en amplitude et en forme) à travers différentes structures forestières. Cela suggère que la variation intra-annuelle de ces indices peut être utile pour distinguer les types de forêts. Il serait donc utile d'analyser la façon dont la variation temporelle diffère selon les types de forêts cartographiés dans les études précédentes.

vi. Comment combiner les approches spatio-temporelles pour améliorer la cartographie de la distribution des types forestiers ?

En ce qui concerne la sixième question de recherche, cette étude a montré que, au moins en théorie, il est possible de cartographier les distributions de forêts tropicales sur la base des modèles distincts de variation spatiale et temporelle (phénologie) de la réponse spectrale de la canopée. Néanmoins, dans le cadre de la recherche effectuée, la question ne pouvait être traitée de façon aussi complète que souhaitée. Bien que la méthode développée soit prometteuse, il y a beaucoup de place pour de nouvelles améliorations et des recherches supplémentaires.

La thèse présentée démontre qu'il est possible de traiter les artefacts des données de télédétection pour examiner les modèles de variation spatiale et temporelle de la réponse spectrale des forêts tropicales. Il a montré que les rythmes phénologiques des forêts tropicales humides peuvent être déduits des données de télédétection et que les types de forêts peuvent être cartographiés en fonction des modèles de réflectance spatiotemporelle des couvertures. C'est donc une contribution importante pour

comprendre l'écologie des forêts tropicales en Guyane et pour améliorer la boîte à outils des scientifiques qui s'intéressent à la dynamique spatio-temporelle des forêts à l'échelle du paysage.

Title: Towards ecologically consistent remote sensing mapping of tree communities in French Guiana: Are forest types identifiable from spatio-temporal canopy reflectance patterns?

Keywords: forest ecology, tropical rainforests, temporal variation, phenology, radiative transfer modelling, Landsat, MODIS, SPOT VEGETATION

Abstract: Tropical forests, which provide important ecosystem functions and services, are increasingly threatened by anthropogenic pressures. This has resulted in an urgent need to understand tree species diversity of those forests. Where knowledge of that diversity is largely from the botanical surveys and local ecological studies, data must inevitably be up-scaled from point observations to the landscape and regional level if a holistic perspective is required. This thesis explores aspects of the spatio-temporal heterogeneity of canopy reflectance patterns over the forests of French Guiana, in order to assess whether this information could help defining an ecologically consistent forest typology.

To gain insight into both the spatial and temporal heterogeneity of French Guiana's forests, instrumental artefacts affecting the satellite data first had to be addressed. Data used in this study represent the spectral response of forest canopies, and the way in which such data are captured makes them susceptible to the 'bi-directional reflectance distribution function' (BRDF). BRDF indicates that objects do not reflect light in equal proportions in all directions (isotropically). Thus, forest canopies will reflect light anisotropically depending on factors including canopy roughness, leaf optical properties and inclination, and the position of the sun relative to the sensor. The second chapter of this thesis examines how BRDF affects the canopy reflectance of forests in French Guiana, and how not correcting for BRDF affects spectral classifications of those forests. When monthly reflectance data corrected for the artefact are examined, these suggest seasonally-occurring changes in forest structure or spectral properties of French Guiana's forests.

The third chapter of this thesis thus examines temporal effects of BRDF, and used cross-regional comparisons and plot-level radiative transfer modelling to seek to understand the drivers of the monthly variation of the forests' canopy reflectance. For the latter, the Discrete Anisotropic Radiative Transfer (DART) model was used along with aerial laser scanning (ALS) observations over different forest structures, indicating that the observed variation in reflectance (and derivatives known as vegetation indices) could not be explained by monthly variations in solar direction. At the regional scale, it was also demonstrated that forests in the Guiana Shield possess temporal variation distinct from forests in central Africa or northern Borneo, forests also lying just above the Equator. Had the observed temporal variation in vegetation indices been the result of BRDF, it would have been expected that the forests in the three zones would have similar patterns of variation, which they did not. Central African forests appear to have their greening synchronized with rainfall, whereas forests in the Guianas appear synchronized with the availability of solar radiation.

Further analysis of the vegetation index time-series of observations also indicated that different types of forests in French Guiana possess distinct patterns of temporal variation, suggesting that tropical forest types can be discriminated on the basis of their respective "temporal signatures." That was exploited in the fourth chapter of the thesis, which maps forests in French Guiana based on their combined spatio-temporal canopy reflectance patterns and by so doing presents a novel way of addressing forest typology, based on ecologically meaningful information.

The thesis presented demonstrates that it is possible to adequately address remote sensing data artefacts to examine patterns of spatial and temporal variation in tropical forests. It has shown that phenological patterns of tropical rainforests can be deduced from remote sensing data, and that forest types can be mapped based on spatio-temporal canopy reflectance patterns. It is thus an important contribution to understand the ecology of tropical forests in French Guiana and to improve the toolbox of scientists dealing with the identification of spatio-temporal patterns observable in forests at the landscape level.

Titre : Contribution à la cartographie des types forestiers de Guyane française à partir de l'analyse des patrons spatio-temporels de réflectance obtenus par télédétection satellitaire

Mots clés : écologie forestière, forêts tropicales humides, évolution temporelle, phénologie, modélisation du transfert radiatif, Landsat, MODIS, SPOT VÉGÉTATION

Résumé : Les forêts tropicales fournissent des services écosystémiques globaux mais sont de plus en plus menacées par la pression anthropique. Il en résulte un besoin pressant de mieux caractériser la diversité biologique (taxonomique et fonctionnelle) de ces milieux. La connaissance accumulée à travers les inventaires botaniques et les études écologiques à l'échelle stationnelle peut être utilement complétée par une approche spatiale intégrative à l'échelle du paysage ou de la région. Cette thèse explore certains aspects de l'hétérogénéité spatiale et temporelle des canopées forestières de Guyane telle que caractérisée par différents capteurs satellitaires en vue de proposer une typologie forestière écologiquement pertinente.

La première étape de ce travail a été d'identifier et de corriger certains artefacts instrumentaux dans les données de télédétection utilisées. L'anisotropie de la réflectivité des couverts forestiers affecte les mesures spectrales. Cette anisotropie est caractérisée par la fonction de distribution de réflectivité directionnelle dont l'acronyme en anglais est la BRDF (*'bi-directional reflectance distribution function'*). La BRDF des couverts forestiers est complexe et dépend notamment de la rugosité de la canopée, des propriétés optiques des feuilles et de leur orientation. Le second chapitre traite de l'importance des effets de BRDF dans les images multispectrales utilisées et des conséquences de leur non prise en compte sur les classifications ultérieures. L'analyse des données mensuelles de réflectance corrigée des effets de BRDF suggère que des changements saisonniers affectant la structure ou les propriétés spectrales intrinsèques de la canopée sont à l'œuvre.

Le troisième chapitre examine plus spécifiquement la contribution d'éventuels effets artefactuels résiduels dans les variations temporelles de réflectance corrigée des effets de BRDF. Deux études sont menées l'une comparative à l'échelle régionale et l'autre sur base de simulation du transfert radiatif. L'étude comparative à l'échelle de la ceinture équatoriale montre des patrons temporels distincts sur le bouclier guyanais, en Afrique centrale et sur l'île de Bornéo. Le « verdissement » des forêts d'Afrique centrale semble synchronisé avec la pluviométrie alors qu'il semble être en phase avec l'évolution du rayonnement solaire disponible en Guyane. Les variations temporelles de géométrie capteur-soleil étant les mêmes pour les différents sites celles-ci ne peuvent être responsables des patrons temporels discordants observés. Dans la seconde étude un modèle de transfert radiatif, DART (*'Discrete Anisotropic Radiative Transfer'*), est utilisé pour simuler des images multispectrales pour les différents mois de l'année à partir de scènes forestières reconstituées par analyse de levés lidar aérien. Les variations temporelles de géométrie capteur-soleil ne permettent pas de retrouver les variations temporelles observées dans les images réelles, conduisant encore à la conclusion que le signal de variation saisonnière de la réflectance est bien réel.

Le quatrième chapitre explore l'intérêt de l'introduction de la variation temporelle de la réflectance de la canopée dans la classification des forêts. L'analyse spatio-temporelle de l'indice de végétation amélioré (EVI) indique que les patrons saisonniers varient spatialement à l'échelle de la Guyane. Une classification basée sur la signature temporelle est proposée et discutée. L'introduction de la signature temporelle saisonnière dans les classifications des couverts forestiers *sempervirens* ouvre des perspectives nouvelles pour la typologie des forêts tropicales humides.

Cette thèse montre qu'il est possible de se prémunir des artefacts instrumentaux liés à la réflectivité directionnelle anisotrope des couverts pour tirer parti des variations saisonnières de la réflectance des canopées tropicales. L'introduction de cette caractéristique du fonctionnement des forêts dans le processus de classification devrait permettre à la fois de raffiner et de renforcer la pertinence des typologies des couverts forestiers tropicaux.