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Sampling and scaling for satellite biophysical product validation from optical sensors with an emphasis on tropical forests

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CONTENTS

KEY TERMS

Geostatistics	Defined by the ESRI GIS dictionary as: "a class of statistics used to analyse and predict values associated with spatial or spatio-temporal phenomena" (ESRI, 2014).
Heterogeneity / homogeneity	To our knowledge there is no statistical definition of spatial homogeneity / heterogeneity however multiple definitions exist for the term (Jacob & Weiss, 2014). It can be described through two components: spatial variability of a property over a scene; and spatial structure resolvable at the sensor's resolution e.g. correlation area (radius define by correlation length – see below) (Garrigues, et al., 2006). In this report we refer only to horizontal homogeneity / heterogeneity.
Spatial autocorrelation and correlation length	The degree to which samples closer to one another are similar/different. Correlation length is a related measure which defines the range at which two samples are not spatially correlated.

1 INTRODUCTION

Quality assured satellite-derived products must be validated against an independent reference. The independent reference must also contain information concerning its quality to ensure that a suitable judgement of the satellite product quality can be made. A satellite product has been through a series of algorithms that convert the raw data value (i.e. the signal recorded in digital numbers) to a parameter related to the Earth's surface (e.g. top of atmosphere radiance, bottom of atmosphere reflectance, leaf area index, etc.). In many cases this involves a series of assumptions about the surface and the state of the atmosphere at the time of the overpass; all of these cause deviations between the product value and the true value when these assumptions do not hold. Therefore, validation of satellite products is imperative if their quality is to be known and the datasets are to be improved.

This report focuses on sampling and scaling exercises for satellite-derived biophysical product validation over tropical forest regions and aims to provide a review of the current techniques and issues within this area. For sampling issues and guidance for integrated systems – those which use all the information together - the reader is referred to the Sampling Design chapter in (Natural Resources Management and Environment Department, 1997).

Tropical forests account for approximately 20 % of terrestrial carbon stocks (FAO, 2001) and play a crucial role in the water and nutrient cycles at the continental scale as well as containing significant biodiversity. Another factor is their importance to humans for timber, food and medicine.

Environmental controls on forest composition mean that forest dynamics can change starkly over small spatial intervals. Rainfall gradients, largely controlled by topography, influence the plant species composition and this causes variation in understorey light availability (Brenes-Arguedas, et al., 2010). Rainforests have complex vertical profiles split into many layers. These are comprised of trees and plants that have adapted to the light availability in that region of the canopy. The vertical profile is optimised sufficiently such that in most canopies less than 5 % of the incoming radiation reaches the forest floor (Torquebiau, 1988; Niinemets, 2010). However, on short temporal scales the canopy and understorey light regimes are controlled by cloud cover, canopy structure and solar geometry (Reifsnyder, et al., 1971; Rich, et al., 1993; Jennings, et al., 1999). In situ monitoring equipment is capable of capturing the temporal dynamics of understorey light conditions, while satellite products are able to capture instantaneous top-of-canopy spatial dynamics over larger areas; as (Running, et al., 1999; Senna, et al., 2005) point out, modelling is needed to account for the remaining unmeasured processes.

Despite the importance of tropical forest ecosystems relatively little is known about them, in contrast with temperate forest ecosystems. In the remote sensing domain, new technologies take longer to reach tropical forest research as a result of the complexity of the environment and infrastructure availability (Sánchez-Azofeifa, et al., 2003). Since many of the global institutions working in remote sensing are based in the temperate areas of the world it is likely that a significant reason for this is convenience; the technology is tested locally and then adapted to rainforests once it is deemed suitable.

With regards to canopy light regimes, limited research has been conducted in tropical forests before the 1990s, for any significant period of time (Rich, et al., 1993). This has meant that the radiative regime of tropical forest canopies and the factors influencing them have only just begun to emerge. In particular, studies looking at the influence of canopy structure on absorption (Gastellu-Etchegorry & Trichon, 1998) and the spatial variation of canopy chemistry (Asner & Martin, 2008; Asner, et al., 2009) aim at identifying the main drivers of (radiative) spatial heterogeneity. Understanding these dynamics is crucial to the interpretation of remote sensing estimates of forest biophysical parameters, but can only be done with long-term monitoring which must include in situ measurements (Senna, et al., 2005). A key factor in this will be the improvement of deployable sensor capabilities and their calibration and characterisation (Sánchez-Azofeifa, et al., 2003).

2 SAMPLING

Satellite-based estimates of biophysical parameters are aggregated over a minimum area equal to the sensor's spatial resolution. In contrast, in situ validation measurements are usually point measurements or at least have a smaller spatial footprint than satellite measurements. The consequence is a mismatch in the spatial scale between the satellite estimates and the in situ measurements. Therefore, the goal of the spatial sampling scheme is to estimate the aggregated value of the parameter using multiple spatially distributed measurements over the study area (Widlowski, 2010). Despite the existence of good practice procedures for sampling (Law, et al., 2008; Fernandes, et al., 2014), it remains a challenge to create aggregated parameter values with a known uncertainty that account for errors in the scaling procedure (Phillips, et al., 2002; Sánchez-Azofeifa, et al., 2011).

The aggregated value derived from the sampling scheme must have one overarching quality: it must be unbiased. This essentially means that the aggregated value does not depend on the location of the samples (Widlowski, 2010). In practice, adequate sampling of the spatial variability (Jennings, et al., 1999; De Wasseige, et al., 2003; Asner, et al., 2009), and the use of an unbiased estimator (e.g. the mean), are suitable for this end (Widlowski, 2010). (Vierling & Wessman, 2000; Baldocchi, et al., 2001) point out that the same is also true of the temporal dimension, where accounting for variability at short time scales is needed for understanding of differences between leaf and canopy scale plant-atmosphere carbon exchange. The importance of unbiased sampling is clear, however there are scenarios where technical constraints mean an inadequate sampling procedure has been or has to be implemented. The possible reasons for this are discussed (see section 2.3), but it is noted by (Phillips, et al., 2002) that these effects will leave signs in the data.

Satellites are able to provide uniformly sampled spatial measurements of the study area (Glenn, et al., 2008); to achieve this same coverage using in situ monitors necessitates high density sampling, which is both costly and time-consuming. Consequently, a key requirement for an in situ sampling scheme is to provide the measurements necessary for an unbiased aggregated value whilst also reducing the cost associated with the sampling i.e. the number of samples needed. As a result, trade-offs between cost and uncertainty form the crux of all validation campaigns (Widlowski, et al., 2006; Martinez, et al., 2010).

2.1 MEASURANDS

The majority of this report discusses sampling and scaling with regards to forest biophysical products that are derived from optical sensors. A summary of LAI and PAR (photosynthetically active radiation) / fAPAR (fraction of absorbed PAR) estimation techniques from both ground sensors (Table 1) and algorithms applied to satellite data are provided (Table 2Table 3). This information is important since even amongst ground-based optical sensors there are a diverse array of techniques used to derive these variables, each applying different technology and model assumptions. Technological differences arise from sensor configuration (i.e. spectral response, angular sampling, etc.), while the model assumptions determine the manner in which the radiative transfer equation is applied. Knowledge of both of these factors is important in determining the optimal sampling scheme for a particular sensor and ensuring that the appropriate measuring conditions are met. Understanding the algorithms employed to derive biophysical parameters from satellite data sets will ensure equivalent quantities from in situ and earth observation data products are being compared.

In this report, LAI is defined as one half of the total green leaf area per unit horizontal ground surface area (i.e. m^2/m^2 – dimensionless units, unless mentioned otherwise) (Chen & Black, 1992; Fernandes, et al., 2014), while PAR refers to the 400 nm – 700 nm radiation waveband that is used by plants to photosynthesise (units of μmol photons m^{-2} s^{-1}). The importance of timely knowledge concerning the LAI and fAPAR of vegetated areas for applications related to climate modelling, agriculture, hydrology and forestry has been recognised by the Global Climate Observing System (GCOS) and as a result they form 2 of the 50 Essential Climate Variables (ECVs). Knowledge of these quantities over tropical forest regions is of particular importance to climate modelling since tropical forest ecosystems are some of the most productive environments on the planet. The current requirements associated with fAPAR and LAI are shown below in Figure 1 and Figure 2 (World Meteorological Organisation, 2011).

Table 1 Common optical techniques for estimating LAI and fAPAR.

Technique	Description	Assumptions	Issues and notes
LAI 2200 (ground)	Optical instrument that measures the intensity of incoming light (two instruments are required) through 5 rings at various sensor zenith angles. The values are used to invert the Beer-Lambert law: $$I = I_o e^{(-k\ LAI)}$$ Where: I = top of canopy intensity, I_o = bottom of canopy intensity, and k = extinction coefficient. The sensor measures intensity at 5 separate angles. See (Bréda, 2003) for more details.	Assumptions are: turbid medium canopy which is homogenous and horizontally infinite; all in the intercepting medium is green leaves; foliage is randomly orientated; foliage elements are small relative to the area of the measurement ring; foliage is randomly distributed; foliage absorbs all radiation (i.e. no transmittance or reflection). See (Bréda, 2003) for more details.	• Cannot be carried out in direct sunlight or uneven sky conditions. • Comparisons between sites need the same sky conditions.
Hemiphotos (ground)	Uses digital hemispherical photography and a classification routine to distinguish between clear sky and foliage occupied sky (gap fraction). This information is used to invert the gap fraction equation: $$P(\theta) = e^{-\frac{G(\theta,\alpha)LAI}{\cos(\theta)}}$$ Where: $P(\theta)$= gap fraction, $G(\theta,\alpha)$ = G-function, θ = view zenith angle, and α = leaf angle distribution. See (Bréda, 2003) for more details.	Assumptions are: randomly distributed leaves (i.e. no clumping); leaf size is small relative to the canopy; all dark objects are leaves. See (Bréda, 2003) for extended discussion.	• Cannot be carried out in direct sunlight or uneven sky conditions. • Sensitive to camera settings (e.g. exposure). • Comparisons between sites need the same sky conditions.
TRAC	Tracing Radiation and Architecture of Canopies (TRAC) is a portable optical instrument that measures the intensity of incoming light along a transect which is used to retrieve gap size distribution and gap fraction. This is used to invert the gap fraction equation and convert effective LAI to LAI. For more details see (Leblanc, et al., 2002).	Assumptions are: everything contributing to gap fraction is leaf (otherwise it should be considered plant area index); no scattering (black leaf assumption).	• Only corrects clumping effects larger than the leaf scale. • Ideally a second instrument is needed to provide a reference reading in a shaded location. • Consideration of operator shadowing is required

PAR sensors and networks	By positioning PAR sensors (hemispherical irradiance sensors calibrated to µmol photons m^{-2} s^{-1}) above and below the canopy the fraction of light absorbed in the photosynthesis bandwidth (400 – 700 nm) can be determined through: $$fAPAR = \frac{PAR^{\downarrow}_{Z>h} - PAR^{\uparrow}_{Z>h} - PAR^{\downarrow}_{Z=0}\left(PAR^{\downarrow}_{Z>h} - PAR^{\uparrow}_{Z=0}\right)}{PAR^{\downarrow}_{Z>h}}$$ Where: ↓ and ↑ refer to incoming and outgoing PAR, $Z = 0$ refers to the position below the canopy and $Z > h$ refers to the vertical position above the canopy (h is the canopy height). This is discussed thoroughly in (Widlowski, 2010).	The approach described in the description column only refers to the 4-flux approach. This approach assumes that all absorption takes place in the canopy (i.e. omitting absorption from soil). Likewise, it is assumed that all absorption in the canopy takes place in the leaves and not from branches and dead plant material.	• Requires four sensors per sample. • Not always possible to place sensors above the canopy.

Table 2. Satellite fAPAR products and a selection of their associated assumptions and issues.

Product	Description	Assumptions	Issues and notes	Sources
CYCLOPES	Uses a neural network (NN) to invert the SAIL radiative transfer model. The NN takes the solar zenith angle (at 10:00 am local time) as well as reflectances in the red, near infra-red and shortwave infra-red bands. The data used for this product is derived from the VEGETATION sensor on-board SPOT.	• Turbid medium canopy (and associated assumptions) • Lambertian surfaces	• Neural networks have little application outside of the range of the calibration data. • Black-sky fAPAR	(Baret, et al., 2007)
POLDER	Derived from a linear relationship between fAPAR and the Renormalised Difference Vegetation Index (RDVI) derived from comparison with SAIL simulations. The product only uses optimal geometric configurations (in the backscattering direction) from the POLDER instruments.	• Assumes simulation is 'truth' • Assumes no residual effects from the soil background are present • Assumes linear relationship and associated uncertainty are applicable globally	• Simulation based on 1D RT model (i.e. turbid medium canopy, Lambertian surfaces, etc.) • Daily fAPAR (i.e. not instantaneous)	(Roujean & Breon, 1995)
LandSAF	Applies the same approach as the POLDER product but uses SEVIRI data as input. However SEVIRI does not have multi angular capabilities so reflectance in optimum geometry is computed following the method of (Roujean, et al., 1992).	• Same as POLDER derived fAPAR with added assumptions associated with the bidirectional reflectance model (i.e. single scattering, etc.)	Same as above	(García-Haro, et al., 2013) and (Roujean, et al., 1992)
GEOLAND2	Uses a neural network trained on a fused product (which is based on a weighted average between CYCLOPES and MODIS fAPAR products) to estimate fAPAR from SPOT-VEGETATION data.	• Fusion is weighted by product uncertainties which are themselves dependent on the product radiative transfer assumptions and method of uncertainty estimation (i.e. not derived from traditional Guide to the Expression of Uncertainty in Measurement (GUM) techniques).	• Neural networks have little application outside of the range of the calibration data. • Issues with MODIS and CYCLOPES products will still be present here (although some biases have been fixed) • Black sky fAPAR	(Baret, et al., 2013)
MODIS	A three dimensional radiative transfer model is used to determine fAPAR. The model is inverted using a look up table (LUT) approach where 5 biomes with distinctly different canopy architecture characteristics are used. fAPAR values are assigned according to how similar the measured and modelled reflectance values are.	• Assumes global vegetated surface can be sufficiently characterised by 5 biomes.	• Black-sky fAPAR • Back-up algorithm uses NDVI-fAPAR relationship	(Knyazikhin, et al., 1999) and (Tian, et al., 2000)
MERIS	This product derives fAPAR from its relationship with the generic vegetation index. This relationship is calibrated using a 1D radiative transfer model which produces coefficients that are utilised for	• Leaf single scattering albedo is fixed • Turbid medium approximation in	• Instantaneous • Green fAPAR • Direct irradiance only	(Gobron, 2011)

	different vegetation cover types.	radiative transfer model		
MISR	The MISR fAPAR product uses a LUT, populated from numerous simulations from a 3D radiative transfer model, to retrieve fAPAR. The observed reflectances (hemispherical-directional & bi-hemispherical) are compared to modelled reflectances; the fAPAR used to compute the modelled reflectances is set as the fAPAR value.	• Assumes global vegetated surface can be characterised by 6 biome types. • Lambertian soil and leaves	• Uncertainty based on the output of the spread of the inversion so may be unrealistic. • Green fAPAR • Instantaneous	(Diner, et al., 2008)
GlobCarbon	Derives fAPAR from a variety of sensors: ATSR-2, AATSR, MERIS and VEGETATION. The algorithm uses reflectance in the red band as input to the above canopy PAR reflectance as well as a 1D representation of canopy absorption which utilises GlobCarbon LAIe.	• Turbid medium approach • BRDF component of reflectance is negligible. • Assumes fixed parameters applicable globally (e.g. light extinction coefficient, light multiple scattering coefficient, etc.)	• Instantaneous • Black-sky fAPAR • Parameterised with GlobCarbon LAIe • Temporal smoothing applied	(Plummer, et al., 2007) & (Lacaze, 2004)
JRC-TIP	Uses the MODIS black and white sky albedos and a 1D radiative transfer model to estimate fAPAR. The algorithm first estimates the model parameters before computing fAPAR using these in a second step.	• Turbid medium approach • Uses an effective LAI • Model is globally representative	• Temporal consistency is achieved using prior PDFs based on previous values of parameters.	(Pinty, et al., 2011) & (Pinty, et al., 2011)

Table 3. Satellite LAI products and a selection of their associated assumptions and issues.

Product	Description	Assumptions	Issues and notes	Sources
CYCLOPES	Uses a neural network to invert the SAIL radiative transfer model. The NN takes the solar zenith angle (at 10:00 am local time) as well as reflectances in the red, near infra-red and shortwave infra-red bands. The data used for this product is derived from the VEGETATION sensor on-board SPOT.	• Turbid medium canopy (and associated assumptions) • Lambertian surfaces	• Neural networks have little application outside of the range of the calibration data.	(Baret, et al., 2007)
POLDER	Uses a neural network to invert (Kuusk, 1995)'s canopy radiative transfer model. The PROSPECT model (Jacquemoud, et al., 1996) is used to describe the leaf optical properties while simple and multiple scattering in the canopy are described by the (Nilson & Kuusk, 1989) and SAIL (Verhoef, 1984) models respectively.	• Turbid medium • Spherical leaves	• Neural networks have little application outside of the range of the calibration data – LAI > 6.5 not sampled.	(Lacaze, 2005)
LandSAF	Based on the relationship between fIPAR (fraction of intercepted PAR) and fVC (fraction of vegetation cover) described by (Roujean & Lacaze, 2002) which states that fIPAR = fVC when the solar zenith and view zenith angle are both 0^{o}.	• Lambertian leaves and soil • Turbid medium canopy • Constant clumping • Spherical leaf orientation assumed applicable to whole MSG disc area.	• Fudge factor (α) to stop artificially high LAI values	(García-Haro, et al., 2013)
GEOLAND2	Uses a neural network trained on a fused product (which is based on a weighted average between CYCLOPES and MODIS LAI products) to estimate LAI from SPOT-VEGETATION data.	• Fusion is weighted by product uncertainties which are themselves dependent on the product radiative transfer assumptions and method of uncertainty estimation (i.e. not derived from traditional Guide to the Expression of Uncertainty in Measurement (GUM) techniques).	• Neural networks have little application outside of the range of the calibration data. • Issues with MODIS and CYCLOPES products will still be present here (although some biases have been fixed)	(Baret, et al., 2013)
MODIS	A three dimensional radiative transfer model is used to determine LAI. The model is inverted using a look up table (LUT) approach where 5 biomes with distinctly different canopy architecture characteristics are used. LAI values are assigned according to how similar the measured and modelled reflectance values are.	• Assumes global vegetated surface can be sufficiently characterised by 5 biomes. • Lambertian soil and leaves	• Back-up algorithm uses NDVI-fAPAR relationship	(Knyazikhin, et al., 1999) and (Tian, et al., 2000)
MISR	Uses a LUT to invert a 3D radiative transfer model based on simulations over different biomes. The algorithm compares simulated and modelled reflectances to derive LAI. MISR has multiple view angles which can be used to constrain the retrieval process. Uncertainties are determined from the spread	• Assumes global vegetated surface can be sufficiently characterised by 6 biome types. • Lambertian soil and leaves	• Uncertainty based on spread of the output of the inversion so may be unrealistic	(Diner, et al., 2008)

	in possible LAI values.			
GlobCarbon	Uses relationships between LAI and the simple ratio and reduced simple ratio indices based on the Four-Scale canopy reflectance model (Chen & Leblanc, 2001).	• Canopy reflectance model based on geometric optics theory (i.e. tree represented as ellipsoids/cones/etc. on sticks). • Assumes global vegetated surface can be sufficiently characterised by 7 vegetation cover types.	• Saturation of relationship at high LAIs. • Uses multiple sources of satellite data. • Uses vegetation cover specific clumping index	(Deng, et al., 2006) & (Plummer, et al., 2007)
JRC-TIP	Uses the MODIS albedo products (black and white sky) with a 1D radiative transfer model to determine the effective LAI. The model inversion is done by comparing modelled and measured values and using the LAI of those that match closely to be the true effective LAI (via a LUT).	• Turbid medium canopy • No clumping • Model is globally representative	• Effective LAI • Temporal consistency is achieved using prior PDFs based on previous values.	(Pinty, et al., 2011)

Requirements defined for *Fraction of Absorbed PAR (FAPAR)* (5)

This tables shows all related requirements. For more operations/filtering, please consult the full list of Requirements

Note: In reading the values, goal is marked blue, breakthrough green and threshold orange

Id	Variable	Layer	App Area	Uncertainty	Stability / decade	Hor Res	Ver Res	Obs Cyc	Timeliness	Coverage	Conf Level	Val Date	Source
277	Fraction of Absorbed PAR (FAPAR)	Land surface	Global NWP	5 % 10 % 20 %		2 km 10 km 50 km		24 h 5 d 10 d	3 h 24 h 10 d	Global land	reasonable	2009-02-10	John Eyre
359	Fraction of Absorbed PAR (FAPAR)	Land surface	High Res NWP	5 % 10 % 20 %		1 km 5 km 20 km		12 h 24 h 2 d	24 h 3 d 7 d	Global land	reasonable	2011-07-29	JF Mahfouf
38	Fraction of Absorbed PAR (FAPAR)	Land surface	Agricultural Meteorology	5 % 8 % 20 %		5 km 13.6 km 100 km		60 min 6 h 7 d	24 h 2 d 5 d	Global land	reasonable	2003-10-20	ET ODRRGOS
566	Fraction of Absorbed PAR (FAPAR)	Land surface	SIA	5 % 7 % 10 %		50 km 100 km 500 km		7 d 12 d 30 d	24 h 3 d 30 d	Global land	firm	2009-01-19	Laura Ferranti
664	Fraction of Absorbed PAR (FAPAR)	Land surface	Climate-TOPC	5 % 7 % 10 %		0.25 km 0.5 km 2 km		24 h 3 d 30 d	10 d 15 d 30 d	Global land	firm	2007-07-19	TOPC

Figure 1. Key information on the state of fAPAR monitoring - screenshot from (World Meteorological Organisation, 2011) – note that uncertainty is given at the 68 % confidence interval (1σ). GCOS requirements state that fAPAR should be collected in two weekly cycles, at 250 m resolution, with 10 % accuracy and 3 % stability (Global Climate Observing System, 2011).

Requirements defined for *Leaf Area Index (LAI)* (5)

This tables shows all related requirements. For more operations/filtering, please consult the full list of Requirements

Note: In reading the values, goal is marked blue, breakthrough green and threshold orange

Id	Variable	Layer	App Area	Uncertainty	Stability / decade	Hor Res	Ver Res	Obs Cyc	Timeliness	Coverage	Conf Level	Val Date	Source
279	Leaf Area Index (LAI)	Land surface	Global NWP	5 % 10 % 20 %		2 km 10 km 50 km		24 h 5 d 10 d	3 h 24 h 10 d	Global land	reasonable	2009-02-10	John Eyre
361	Leaf Area Index (LAI)	Land surface	High Res NWP	5 % 10 % 20 %		1 km 5 km 40 km		12 h 24 h 2 d	24 h 3 d 7 d	Global land	tentative	2011-07-29	JF Mahfouf
397	Leaf Area Index (LAI)	Land surface	Hydrology	5 % 8 % 20 %		0.01 km 0.1 km 10 km		7 d 11 d 24 d	24 h 41 h 5 d	Global land	reasonable	2003-10-20	ET ODRRGOS
41	Leaf Area Index (LAI)	Land surface	Agricultural Meteorology	5 % 7 % 10 %		0.01 km 0.1 km 10 km		5 d 6 d 7 d	24 h 41 h 5 d	Global land	reasonable	2003-10-20	ET ODRRGOS
674	Leaf Area Index (LAI)	Land surface	Climate-TOPC	5 % 7 % 10 %		0.25 km 0.85 km 10 km		24 h 3 d 30 d	30 d 45 d 90 d	Global land	tentative	2007-07-19	TOPC

Figure 2. Key information on the state of LAI monitoring – screenshot from (World Meteorological Organisation, 2011) – note that uncertainty is given at the 68 % confidence interval (1σ). GCOS requirements state that fAPAR should be collected in two weekly cycles, at 250 m resolution, with 20 % accuracy and 10 % stability (Global Climate Observing System, 2011).

2.2 SENSOR PERFORMANCE AND USAGE CONSIDERATIONS IN TROPICAL CONDITIONS

Tropical forests are harsh environments for electronic equipment mainly as a result of high relative humidity, high temperatures and frequent rainfall (Pastorello, et al., 2011). The sky conditions may also confuse interpretation of the retrieved values. In particular, many instrument manufacturers emphasise the use of diffuse sky conditions due to the reduction in radiative variability (Widlowski, 2010); in the context of satellite validation sky conditions similar to those existing at the time of overpass are mandatory (Widlowski, et al., 2006). Radiative variability arises from changing solar angles under non-diffuse conditions meaning that sunflecks migrate through the canopy and forest floor reaching the below canopy sensors (Vierling & Wessman, 2000).

Optical sensors are known to be sensitive to changes in temperature and as a result PAR sensor manufacturers typically specify the likely effect of changes in temperature on the response of the instrument (e.g. (0.06 ± 0.06) % per ^{o}C for the Apogee SQ series (Apogee Instruments, 2013)). Over wide temperature ranges this effect can be significant. The instrument response to changing humidity is less clear and is complicated by the fact that performance degradation due to water marks and dirt accumulation is likely to occur (Jennings, et al., 1999) for sensors that are left outside for prolonged periods. Likewise, sensor breakages are also more likely given the abundance of animals and insects, while water from the frequent tropical downpours is likely to cause equipment failure if the environmental housing of those instruments is compromised (e.g. see (Rich, et al., 1993)). Under the traditional data gathering routine (i.e. leave the sensors out and collect the data at the end) these issues would only be discovered once the researcher has visited the plot again. One solution to enable identification and tracking of potential errors is through the use of wireless sensor networks as proposed by (Pastorello, et al., 2011). By combining this with characterisation of the sensors before, during and after deployment potential environmental effects (e.g. aging) can be corrected.

2.3 SAMPLE DESIGN

As mentioned previously, the main goal of in situ sampling for satellite product validation is to provide aggregated unbiased estimates of the same target quantity. The sampling design is pivotal to this effort (Widlowski, et al., 2006), something which has been tested (e.g. (Leuschner, et al., 2006)), and recognised at national and international level for forest inventories (McRoberts, et al., 2013). Sample design should be based around the study goal, the characteristics (including uncertainty) of the sensor to be validated, and the cost (Leuschner, et al., 2006; Martinez, et al., 2010; McRoberts, et al., 2013); if these points are not adequately taken into consideration, the risk is that the chosen sampling regime will not be applicable to the phenomena under investigation (e.g. as in part of (Clark, et al., 2008)).

Commonly used sample designs include random, systematic and stratified random sampling (a brief description of each is provided in (Martinez, et al., 2010)). These approaches are standard techniques that are recommended providing prior knowledge of the background environment is minimal or not available. However, to build on this to something approaching an optimal solution, prior information on the environment and the cost criteria are required (McRoberts, et al., 2013). An example of a formulation of this problem would be to maximise the variability sampled in the spatial field while reducing the number of sample locations needed; in this case minimising the number of sensors would be the cost criteria.

(McRoberts, et al., 2013) describe the role of two sampling approaches: purposive and probability. The former is used to describe schemes that deliberately select convenient sites; selection based on experience; and methods using optimal criteria. The latter describes any technique utilising probabilistic methods. The authors state that the main advantage of probabilistic methods is their objective nature which makes them more attractive for comparison between other plots and in defending the data gathering process. Likewise, choosing plots or sample sites based on experience increases the likelihood of ‘researcher’ bias (Condit, 2008) such as that described in (Malhi, et al., 2002; Phillips, et al., 2002). (Wulder, et al., 2012) mention that the purposive schemes (described as 'model-based' in their review) are better placed to assess the efficiency of sampling schemes and estimators (e.g. of aggregated values).

Landscape scale determination of biophysical parameters poses further problems due to the sheer area that needs to be covered by in situ measurements. A common approach to this issue is to employ a sampling hierarchy where plots are setup and sampled. The aggregates for each plot are then used to determine the landscape-aggregated value. Depending on the parameter of interest it is sometimes necessary to use subplots within each plot. The manner in which plots within the landscape, and subplots within plots, are distributed is open to the same considerations as described (and to be described) for point samples within those.

In many cases, sampling protocols exist for particular instruments and/or variables. The GCOS (Law, et al., 2008) and ICOS (draft - (Gielen & Op de Beeck, 2014)) reports are key examples of this. However, it is important to recognise that these have been designed to measure specific components and with specific overall goals in mind. Both reports refer specifically to the standardisation of field data procurement for measurands to do with the carbon cycle. In each, a prescriptive account of the way in which each plot should be laid out is described, often with predetermined values (e.g.. 3 m from plot centre). A general issue with sampling protocols is that they attempt to fit a standardised methodology to a potentially diverse group of sites; this means that site quirks cannot be accommodated. (Gielen & Op de Beeck, 2014) do provide some basic scenarios under which the sampling scheme may be modified e.g. if the surrounding vegetation is too heterogeneous, but there is no mention of the manner in which the heterogeneity is to be measured.

Targeted sampling schemes that allow comparison between sites, whilst also incorporating information specific to each site, tend to focus on ways of assessing the full variability of the parameter value in space (De Wasseige, et al., 2003; Clark, et al., 2008). For example, by using a stratified sampling scheme the user is allocating a proportion of the sample points to specific regions in space, and by proxy, specific regions in parameter space that are considered to be significantly different from other regions, as well as important to the global population. Similar activities include positioning samples along environmental gradients (Clark, et al., 2008) or using proxies to estimate the likely variability of the spatial field (e.g. using NDVI – normalised difference vegetation index – to estimate variability in fAPAR). It is worth noting that simple sensitivity analyses such as that described in (De Wasseige, et al., 2003) allow assessment of the impact of spatial uncertainty on the target quantity. A common feature of a number of studies is the use of transect sampling over small periods of time to gain a priori information that can be used in the formulation of the final sampling scheme. This is tailored to the effect under consideration (e.g. correlation, positional accuracy, etc.).

Spatial independence is another factor that is commonly built into sampling schemes (McRoberts, et al., 2013). Correlation between sample points decreases the efficiency with which global values can be obtained and therefore distributing sensors such that each is beyond the maximum correlation length of every other allows a wider area to be covered with fewer sensors. The factors influencing the correlation length depend on the variable of interest. With regards to radiative quantities, the canopy height and density, and solar angle are likely to alter the correlation length, with the latter changing over the course of the day and height in the canopy (Vierling & Wessman, 2000). The natural response to this would be to determine the correlation length during satellite overpass periods and select the longest. Finally, it must be recognised that spatial correlation may be anisotropic i.e. that correlation lengths are not the same in every direction.

Designs tailored to specific goals and areas are often complex. As a result, assessing the validity of these designs is difficult (Wulder, et al., 2012). There are also some unavoidable truths, such as the need for greater sample numbers when high variability is present and/or greater precision is needed (Jennings, et al., 1999).

Many of the issues surrounding non-statistical sample designs relate to the possible introduction of biases. (Malhi, et al., 2002; Phillips, et al., 2002) describe scenarios which would lead to biases in tropical forest biomass estimation as a result of sample placement. Such examples include preference for the selection of 'majestic' forest (so called 'majestic forest bias') – leading to low biomass change if all the plots selected are old growth - or conversely, if there is a preference for plots containing young trees then there may be an increase in biomass over time that may be uncharacteristic of the whole population. Similarly, the preferential selection of areas of forest with similar structure may result in biases of radiative quantities such as those arising from horizontal fluxes (Widlowski, et al., 2006; Clark, et al., 2008).

In many cases it is not possible to place sensors or make measurements exactly according to a predetermined statistical design. There are a number of reasons why this would be the case: obstructions in the field of view of sensors (Pastorello, et al., 2011); errors in the recorded position of sensors/measurements (McRoberts, et al., 2013); site access (De Wasseige, et al., 2003; Condit, 2008; McRoberts, et al., 2013); environmental effects on the instruments (Asner & Martin, 2008); access to the canopy (Leuschner, et al., 2006); effects of canopy height (Clark, et al., 2008; Köhler & Huth, 2010; Widlowski, 2010); species diversity (Clark, et al., 2008; McRoberts, et al., 2013); to name a few.

Wireless sensor networks are starting to be utilised for environmental monitoring and offer an attractive solution for removing cables, obtaining data and detecting sensor faults in real time. Of particular interest is their ability to monitor continually: capturing temporal dynamics at prescribed resolutions and enabling collection of coincident validation data to be used for satellite products. Unfortunately, even these solutions are restricted in their deployment since sensor distribution (in this case distance from one to another) depends on the obstruction density (usually from trees) and local topography which influence the propagation of the radio signal (Pastorello, et al., 2011; Sánchez-Azofeifa, et al., 2011). However, since other in situ monitoring techniques have the same issue their uptake appears inevitable with the introduction of cheaper and more robust technology.

2.4 NUMBER OF SAMPLES

Coupled with the sample distribution is the number of samples deployed. The number of samples controls the magnitude of the uncertainty associated with random effects that is attached to the global value, with larger numbers decreasing the uncertainty. Consequently, deployments involving small numbers of sensors relative to the resolution of the sensor and extent of the study area should be avoided (Widlowski, 2010). In order to determine the number of samples needed n, (De Wasseige, et al., 2003) provide a formula based on the standard deviation of an initial estimate from the area of interest σ_s, the value from a two-tailed student's t-test t, and an acceptable level of error e:

$$n = \left(\frac{\sigma_s t}{e}\right)^2$$

A plot showing the relationship between error and number of sample points is shown in Figure 3 from the results of (De Wasseige, et al., 2003) and highlights two issues. The first is that which has already been mentioned, the error is controlled by the number of samples. The second is that the error does not keep decreasing indefinitely; this means that eventually the cost of greater sample numbers outweighs the decrease in error.

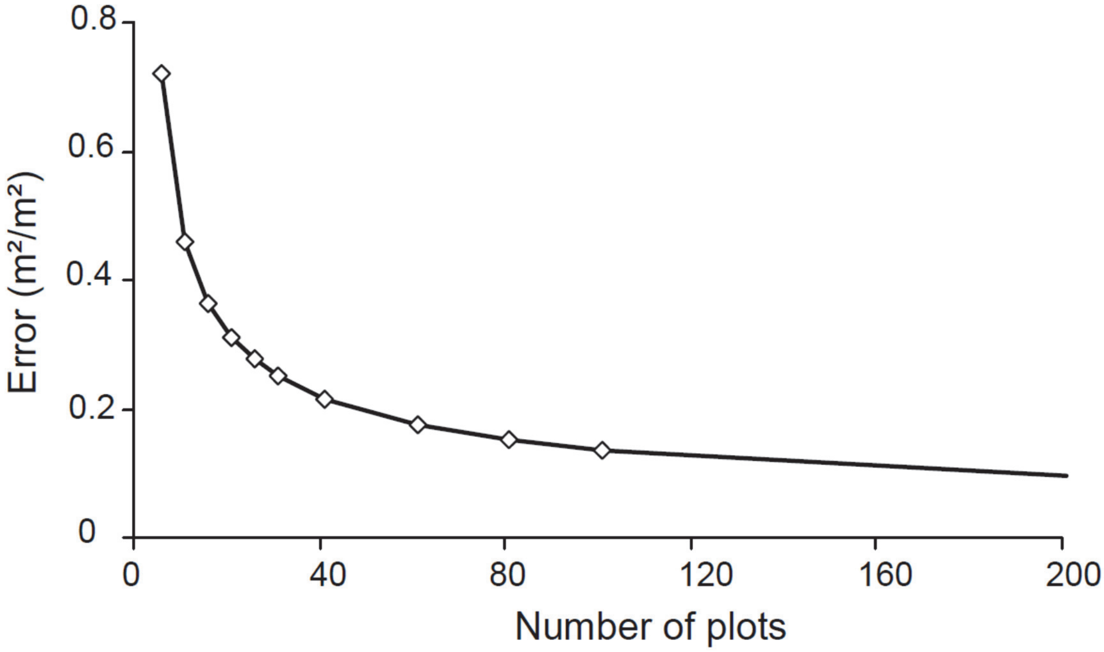

Figure 3 shows the relationship between the number of samples and error in LAI – from (De Wasseige, et al., 2003).

As with the distribution of sensors, the number of sensors/measurements required for appropriate statistics is balanced against the cost of making the measurements (Widlowski, 2010). In most cases the cost aspect is monetary (more sensors/measurements = more money/more time in the field), however it may also refer to the amount of data generated (more samples = more data) (Vierling & Wessman, 2000; Pastorello, et al., 2011; Wulder, et al., 2012) and ability to retrieve it. With the latter point, wireless sensor networks become suitable replacements for traditional data logger systems whereby the data is transmitted to a server negating the need to return to the loggers to access the files. A data analytics framework (i.e. on-the-fly processing) can then be used to manage and process the incoming data stream thus providing more timely results.

3 SCALING

The term 'scale' refers to a combination of both the resolution and extent of an observation; scale refers to the "window of perception" (Wu & Li, 2009, p. 1769). Scale can be applied to any dimension or combinations thereof, such as spatial (x, y, z), spectral, temporal, etc. In this report the focus is primarily on the spatial scale unless it is mentioned otherwise. The Earth's surface, as seen from a satellite sensor, has different spatial features depending on the scale they are viewed at. A classic example of this is in classification problems over forests: at 1 km resolution a forest may look uniform, whereas at 1 m resolution each pixel corresponds to only part of a tree, possibly mainly branch or mainly leaves; as a result the 1 m resolution image has finer structure than is visible from the 1 km resolution image. The ramifications of this are that algorithms or studies designed using data from one scale may not be applicable in another (Wu & Li, 2009).

As scale has been loosely defined above, the term 'scaling' can be defined as the process of changing scale, where upscaling refers to changing from finer detail to coarser detail and downscaling refers to the opposite. In terms of vegetation biophysical parameters, upscaling from the leaf level to canopy integrated quantities is a regular requirement for large scale vegetation monitoring.

By using data acquired from sensors measuring at different spatial scales an attempt is made to isolate unique information from both sources. In many cases it is simply that coarser resolution sensors can view a larger area with less data points, while finer resolution sensors provide the greater detail. In this sense, validation of satellite biophysical products uses observations derived at a finer scale to check those acquired at a coarser scale. In order for this to be applicable, one of the data sources has to be converted to the scale of the other, usually by upscaling the dataset obtained at the finer scale.

The method of scaling depends on the datasets available and ranges in complexity. In the case of point samples there are various geostatistical techniques, such as kriging, which estimate values at unsampled locations; the resulting area can then be compared with satellite-based estimates on a (product grid) pixel by pixel basis. The results of such techniques have brought mixed conclusions as to their quality in vegetated landscapes (see the contrasting opinions of (Weiss & Baret, 2011) and (Martinez, et al., 2010) on the use of kriging for determining values at unsampled locations).

One example of an upscaling technique used in satellite validation (e.g. in VALERI and BigFoot projects) is found in (Weiss & Baret, 2011) and summarised here. Essentially, this technique involves the setup of Elementary Sampling Units (ESUs) whose size and distribution depend on the vegetation type being monitored. The ESUs are sampled with a ground measurement device and a transfer function is fitted between the ground measurements and a coincident satellite image (of similar spatial resolution and whose signal is related to that of the ground measurements). The parameter surface provided by the fitting is then compared by degrading its resolution to that of the satellite data product.

For satellite to satellite scaling where relatively uniformly sampled surfaces are available, averaging over the area of a pixel in the coarser data seems to be the preferential approach; the exception to this is when the relationship between remote sensing signal and biophysical parameter is non-linear as well as the surface being heterogeneous (Jacob & Weiss, 2014)). Other approaches, including more complex examples are discussed in (Wu & Li, 2009).

For validation activities, as in the case of the ESU approach discussed by (Weiss & Baret, 2011), scaling relies on a certain degree of spatial homogeneity. Heterogeneity in the variable of interest is problematic as it signifies that the variance is a function of location and not the same as the global value. In order to alleviate this, the placement (Weiss & Baret, 2011) and number (Widlowski, 2010) of ESUs should be related to the variability of the landscape; in many cases, stratification into multiple areas that individually can be considered as homogenous is the easiest solution (Wang, et al., 2012).

A further issue is that natural forest ecosystems (for various parameters) are often controlled by multiple driving factors. Examples include climate (and microclimate), soil fertility, canopy structure (Asner & Martin, 2008), topography and the history of disturbance (Clark, et al., 2008). As a result, sampling of the forest site may not sufficiently capture the existing gradients. A pragmatic approach would be to select those likely to have the greatest influence on the parameter of interest or undertake pilot sampling campaigns to determine the likely influence of each.

Since it is common to sample a series of plots within a larger region, scaling also requires that the dimensions of each plot (and also the larger region) are suitable for use with any aerial or satellite remote sensing data (De Wasseige, et al., 2003; McRoberts, et al., 2013), i.e. that the minimum resolution of the sensors that are used should be considered before designing the sample scheme.

Changing scale through spatial aggregation has been shown to result in significant model biases (El Maayer & Chen, 2006) while applying algorithms designed at one scale to another can result in violations of the assumptions inherent in the algorithm used, as in the case of fAPAR which is thoroughly discussed in (Widlowski, et al., 2006). Thus failure to scale properly may result in different conclusions being made about the variable of interest (Wu & Li, 2009).

A final point to consider in the scaling of biophysical parameters is the definition of the parameter of interest and the definition of the products used as representations of that parameter. It is clear from Table 1, Table 2 and Table 3 that there are some significant differences in the assumptions employed amongst different satellite products and ground measurement techniques. One example of this is the assumption employed by a number of the in situ LAI techniques: all objects in the canopy are leaves and these are randomly distributed. In this case we know that the first doesn't hold (in forest canopies) while the second is very canopy dependent, yet the technique is widely used to validate satellite LAI data products (among other things) due to a lack of suitable alternatives. The result is that we are comparing an effective LAI (i.e. assuming random leaf distribution) which would be better defined as an effective PAI (random distribution plant area index) to a satellite LAI which more closely corresponds to an effective LAI (product algorithms use spectral information to remove the woody component). This leads to disparities arising solely out of differing retrieval assumptions. Comparison of LAI/fAPAR satellite products from different providers will have a similar effect.

4 CONCLUSION

It is well known that as the number of samples increases so the resources needed to carry out the sampling must increase proportionately. Therefore it is necessary to plan out the sampling scheme and ascertain as much information about the study area and parameter of interest as is possible. Important issues to bear in mind include:

- the variability of the parameter of interest over the study area (higher variability = higher sample numbers);
- the spatial distribution of the variability, i.e. it may be better to stratify the site into distinct regions of similar variability and target resources appropriately;
- the correlation length of the study area to determine the minimum distance at which samples should be placed from each other;
- environmental gradients which may affect the variable of interest; and
- for satellite and airborne validation campaigns: consideration of the viewing conditions of the sensor.

In essence, it can be summed up as requiring: 1) knowledge of the variation, and 2) statistical techniques to deal with the variation (Condit, 2008).

For image to image scaling it is important to remember that aggregation to coarser resolutions reduces the image variability (Garrigues, et al., 2006) in potentially complex ways (i.e. depending on image heterogeneity, etc.). Therefore more complex techniques (not described in this document) which preserve the statistical properties of the two images could be considered instead.

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