GROSS PRIMARY PRODUCTIVITY ESTIMATION USING MULTI-ANGULAR MEASUREMENTS FROM SMALL SATELLITE CLUSTERS

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ABSTRACT

Gross primary productivity is an excellent metric of how much forests act as carbon dioxide sinks but currently have up to 40% uncertainty in their global estimates. A large proportion of the uncertainty has been attributed to artifacts in the sun-sensor geometry of monolithic spacecrafts leading to insufficient sampling of the bi-directional reflectance of vegetation. This paper proposes to use small satellite clusters with spectrometers as a new measurement solution to improve angular sampling locally and scale up measurements globally. Initial observing system simulations with four satellites launched as secondary payloads via the ISS and operating in different imaging modes show error estimates of less than 12% when compared to dense airborne measurements, a 50% improvement to the worst case error produced by corresponding monoliths.

***Index Terms*—** BRDF, satellites, constellation, PRI

1. INTRODUCTION TO THE SCIENCE PROBLEM

Quantifying the extent to which forests and vegetation act as a sink for atmospheric carbon dioxide is very important to estimate carbon feedbacks of vegetation in response to global climate change [1]. Deforestation and forest degradation accounts for 12% of anthropogenic carbon emissions, which have nearly doubled in the past 30 years[2]. Current Gross Primary Productivity (GPP) estimates show uncertainties up to 40% in the terrestrial carbon uptake [3]. GPP is the product of photosynthetic efficiency (ε) and photosynthetically active radiation (APAR) absorbed by the plant. In recent studies, we have shown that measurements of vegetation reflectance at multiple angles can be used to estimate changes in protective leaf pigments as a function of shadow fraction [4]. These protective leaf pigments (xanthophylls), regulate light use efficiency in leaves and can be measured by means of the Photosynthetic Reflectance Index (PRI), a normalized difference index that is sensitive to the xanthophyll absorption at 531nm. Photosynthetic efficiency is the differential of PRI with respect to the shadow fraction [4],[5]. This differential can be estimated from the bi-directional reflectance function (BRDF) of PRI. BRDF describes the directional and spectral variation of reflectance of an optically thick surface element at any instant of time; it is a function of the material surface properties and roughness [7].

Measurement of the BRDF of PRI is inaccurate using existing space-borne sensors. Existing imaging spectrometers such as MODIS or MISR in sun-synchronous orbits, provide insufficient angular coverage during a single overpass. Recent studies have also shown an overestimation of the greening of Amazon forests during the dry season due to seasonal artifacts in MODIS' sun-sensor geometry[8]. Global and frequent BRDF is impractical to estimate using towers and airborne instruments. Therefore, small satellite clusters on repeat track orbits with VNIR spectrometers have been proposed for the purpose [9]–[11]. Usage of angular reflectance data from the CHRIS instrument on the PROBA spacecraft has shown to bring GPP estimation errors down to 10% [3], however PROBA is not designed to measure GPP and does not provide the temporal resolution and global coverage required to do so. One possible solution would be to use constellations of CubeSats to obtain measurements of GPP with a frequent temporal repeat and global coverage [5],[9],[10].

2. CLUSTER EVALUATION METHODOLOGY

This paper proposes a new measurement solution to make multi-angular reflectance measurements using small satellites in close formations called clusters. It uses an observing system simulation experiment (OSSE) to demonstrate the potential improvement in GPP estimation using the new solution and design the most optimal cluster architecture. An architecture is defined here as a unique combination of orbits for the satellites in the cluster. Data from airborne campaigns of the Cloud Absorption

Radiometer (CAR) instrument is used as "truth" data [14]. The CAR is designed to scan from 5° before zenith to 5° past nadir, corresponding to a total scan range of 190°. Its 14 bands are located between 335 and 2344 nm. By flying the CAR (on platforms such as NASA P-3B) around a particular ground spot in circles and at different heights, it is possible to get thousands of multi-angular and multi-spectral radiance measurements used for the accurate estimation of BRDF [14] [15].

OSSE simulations for different cluster architectures output viewing geometries for different geographic locations over a period of time and the true data is locally sampled based on these views. BRDF models are then used to reconstruct reflectance at all angles – measurement zenith and azimuth for a given solar zenith - from the data sample. The error between the BRDF estimated using the reconstructed reflectance versus the true data, and the corresponding error in PRI, quantifies the goodness of the angular viewing geometries. The goal of this paper is to show that with a few satellites, hosted payload launches and simple orbit maintenance, GPP estimation errors are reduced below the current 40% to up to 10%, as demonstrated locally using CHRIS/PROBA data sets[3].

3. OBSERVING SYSTEM SIMULATIONS

Multiple satellites in a cluster were simulated to estimate BRDF and PRI using a simple observing system simulation experiment for each cluster architecture. Earlier studies have provided insight into the launch and maintenance capabilities of clusters with differential orbital elements[10], [16]. Differential semi major axis breaks the cluster and differential inclination or eccentricity is impossible to maintain with current cubesat propulsion technology. The only differential element variables between the satellites are mean anomaly (MA) and the right ascension of the ascending node (RAAN). Each architecture is therefore a function of number of satellites, their differential RAAN and MA and the orbit of the chief satellite.

Our simulations below show that 4 satellites whose MA or RAAN are separated by a few degrees are collectively capable of estimating the full BRDF of vegetated regions within 12% of CAR's measured BRDF. This "gold standard" BRDF, used for validation, was collected over Southern Africa by CAR during NASA's SAFARI campaign in 2000 [15] and has been used to represent the BRDF for all of vegetated Africa in our OSSE. Figure 1-bottom left shows the truth data as a function of the measurement zenith angle (radius) and relative azimuth angle with respect to the run (polar azimuth), for a given solar incidence (27^{o}). The hotspot is apparent in the backscattering direction and is an important feature which the collective cluster is required to capture. Traditional BRDF models such as the RossThick-LiSparse (RLTS) model [13],[14] have been shown to produce less than 0.05% inversion errors when fitted to a dense sample of BRDF measurements [10]. Thus, the majority of the BRDF errors will be due to sub optimal sampling of the BRDF angular plane.

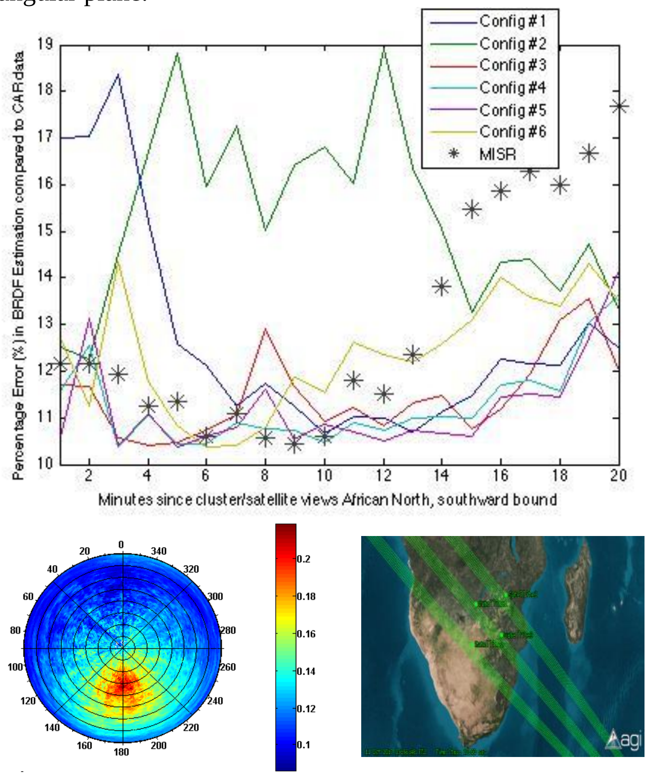

Figure 1: Top - BRDF error in % over time as the 4 satellite cluster (different colors represent different architectures) flies over Southern Africa. The errors are calculated with respect to reflectance (BRDF) measured by CAR during NASA's SAFARI 2000 campaign. The black stars represent BRDF error, calculated in the same way, by MISR (from Two Line Element data) half an hour before in time. Bottom left – CAR collected BRDF in the 682 nm band. Bottom right - Image of the satellite cluster Config #3 as it flies over Southern Africa.

Six architectures of varying differential RAAN and MA among 4 satellites are compared in Figure 1 over the 20 minutes that they take to fly over Africa, southward bound, assuming the BRDF signature over the African subcontinent to be as measured in SAFARI. The chief orbit is assumed to be at ISS inclination and altitude to tap into easy opportunities for ride-share launches. The RMS errors represent the difference between CAR measurements and satellite measurements from the best (red, Config#3) and worst (blue, Config#2) configurations as well as those by MISR's configuration (black stars). The best cluster configuration – with only four satellites and no onboard propulsion - shows errors equivalent to or better than MISR. MISR is used instead of MODIS because of its shorter period of multi-angular data acquisition, therefore more reliable for temporally changing targets.

In all the above configurations, the reference satellite is the same over the 20-minute period and looks nadir, while the other 3 satellites look at the reference satellite's nadir as they move relative to it. Figure 2 shows the effect of changing the reference satellite for one of the worst case configurations. If the 4th satellite (red) is used as reference for the first 6 minutes, followed by the 1st satellite (blue), the estimation error is better than that produced by MISR (stars) for most of Africa. The errors improve from 18% to 12%. The minimum of estimation errors in Figure 2 (black line) can be achieved by controlling satellite attitudes to change the reference satellite, therefore allowing even the sub-optimal architectures (e.g. Config#1) to perform optimally.

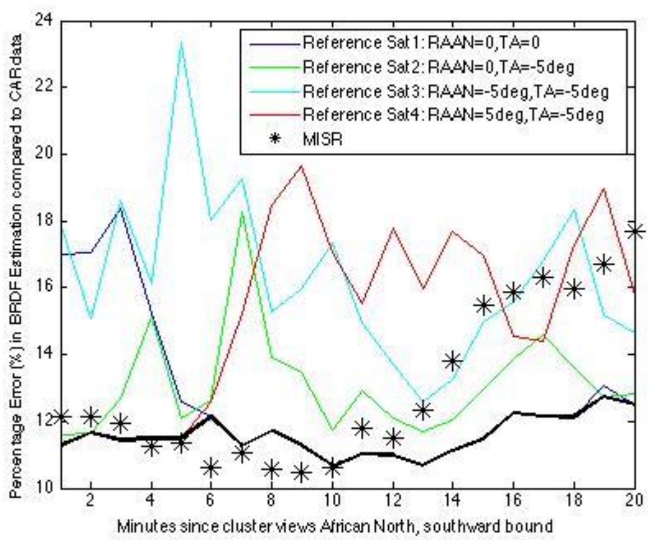

Figure 2: BRDF Error in % over time for the cluster Config#1 in Figure 1a as the 4 cluster satellites – differential orbital elements shown - are individually used as the reference, and the others look at the ground spot at its nadir. The thick black line shows the minimum estimation error, possible using the corresponding satellite as reference.

Errors in BRDF estimation map into errors in PRI estimation. PRI is expressed as the normalized difference of reflectance at a xanthophyll-insensitive reference band to the 531 nm band[19].

$$PRI = \frac{\rho_{531nm} + \rho_{682nm}}{\rho_{531nm} - \rho_{682nm}}$$

Equation 1

The reflectances are expressed in the RLTS model[19]. Since the CAR SAFARI data set does not contain the 531 nm band, a Gaussian variation of the 682 nm band is used as truth. First-Order, second-moment (FOSM) propagation of uncertainty for nonlinear functions is used to statistically map the uncertainty of reflectance in either spectral band to the uncertainty of PRI. By definition of FOSM, the variance of a dependent function is a function of the variances of its variables and its partial differential with respect to them. PRI variance can therefore be represented as a function of the reflectance variance at the 531nm and 682nm bands.

$$\sigma_{PRI}^2 = \left(\frac{\partial PRI}{\partial \rho_{531nm}} \bigg|_{mean(\rho_{531nm})} \right)^2 \sigma_{\rho_{531nm}}^2 + \left(\frac{\partial PRI}{\partial \rho_{682nm}} \bigg|_{mean(\rho_{682nm})} \right)^2 \sigma_{\rho_{682nm}}^2$$

Equation 2

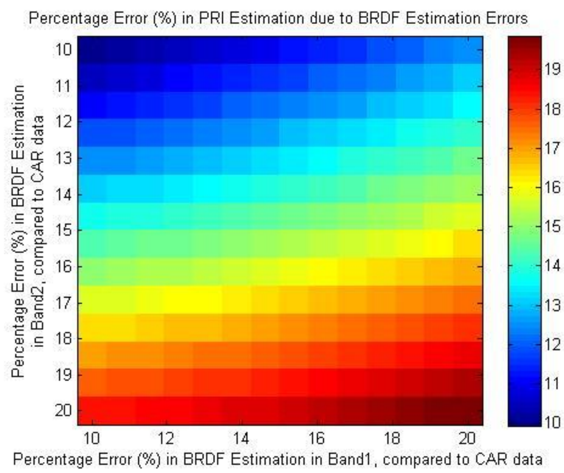

Figure 3: PRI Error in % as a function of BRDF error in the xanthophyll sensitive vs. insensitive bands for true reflection difference of 50%, calculated using first order second moment analysis of uncertainty.

The maximum PRI estimation error varies from 10% to 20% as the difference in true reflectance at 531 nm is assumed to be between 90% to 50% because of inverse proportionality. Figure 3 shows dependence of PRI estimation errors on the BRDF estimation errors in the two spectral bands as calculated using FOSM. Since the BRDF signature of vegetation is similar across different bands, the correlation between the undersampling errors is likely to be high therefore architectures will be concentrated, in the most part, the top left or bottom right of Figure 3. The PRI estimation improvement is apparent - while the monolithic configuration (MISR) shows upto 18% PRI errors, clusters (with changing reference satellites using attitude control) can bring this error down to 6% due to better angular sampling of the BRDF polar plane. Further, since photosynthetic efficiency (ε) is a linear function of PRI, which linearly maps to GPP for a statistically determinate APAR, similar values of error improvement are also expected in GPP estimation.

4. SUMMARY AND FUTURE WORK

This paper shows initial results of the impact of using satellite clusters in formation flight, 4 satellites and without the necessity of propulsion, on BRDF and PRI vegetation. CAR airborne data has been used as the golden standard for BRDF estimation and analytically modified to show its impact on PRI. Adopting the optimal architecture or dynamically changing the reference satellite in orbit leads to reduction in PRI errors by up to a third that provided by MISR, when compared over some fractions of the orbit. Since the CAR instrument does not have the xanthophyll sensitive band, future work includes the use of tower data for more detailed analysis followed by a full trade study of GPP error improvement as a function of number of satellites and their orbital orientations. Tower data is available from from the automated, multi-angular, spectro-radiometer platform called AMSPEC[19] that allows observations in a 330° view area around the tower and the trade study tool as been developed on the MATLAB and Systems ToolKit software platform. Satellite clusters therefore hold great promise in GPP estimation locally and can be scaled up globally by launching more satellite clusters (scalable with more imaging demand). They can provide better understanding of forest cover and corresponding contribution to carbon dioxide emissions.

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