**Validation of vegetation biophysical variables retrievals from The Simplified Level 2 Product Prototype Processor (SL2P) and Landsat-8 data**

1. Introduction

Long-term records of vegetation variables is a crucial international requirement facing accelerated global climatic, environmental and anthropic changes (). Medium resolution multispectral imageries have been identified for systematic mapping vegetation biophysical variables at global scale ().

Several operational models have been developed to retrieve vegetation biophysical variables from remotely sensed optical images, including radiative transfer model (RTM) inversion, statistical approaches, and hybrid techniques. ~4-days leaf area index (LAI) global products are made available using data from Moderate Resolution Imaging Spectrometer (MODIS). However, although MODIS vegetation products sufficiently met the GCOS temporal requirements of ~10-days, they do not satisfy the spatial resolution requirement of 10-m.

As a part of the Global Monitoring for Environment and Security (GMES) space segment, Sentinel-2 mission, offering an unprecedented combination of systematic global coverage of land surfaces, a high revisit of five days, a high spatial resolution, and a wide field of view for multi-spectral, is designed to provide satellite data that can be used to map widely used land surface variables including leaf area index (LAI), fraction of absorbed photosynthetically active radiation (fAPAR), and to complement pre-existent comparable satellite missions such as SPOT and Landsat to ensure continuity.

The key mission objectives for Sentinel-2 are: (1) To provide systematic global acquisitions of high-resolution multi-spectral imagery with a high revisit frequency, (2) to provide enhanced continuity of multi-spectral imagery provided by the SPOT (Satellite Pour l'Observation de la Terre) series of satellites, and (3) to provide observations for the next generation of operational products such as land-cover maps, land change detection maps, and geophysical variables.

For instance, Sentinel-2 (S2) Mission is a constellation of 2 satellites (S2A and S2B) carrying quasi-identical medium resolution Multispectral Instrument (MSI), lunched by the European Space Agency to answer for internation requirements which includes spatial resolution observations from 13 bands in the visible, near infrared and short wave infra-red part of the electromagnetic spectrum.

Globally applicable algorithms for deriving variables from medium resolution imagery generally rely on the inversion of radiative transfer models by matching modelled and observed top-of-canopy bi-directional reflectance (hereafter ‘reflectance’) given acquisition geometry and ancillary information such as land cover (Baret and Buis, 2008). Improvements in satellite data records, radiative transfer models, inversion algorithms and strategies for integrating priors related to land cover or canopy growth stage have resulted in an increasing number of algorithms that satisfy users uncertainty requirements when their underlying assumptions are applicable (Chen, 2018; Croft and Chen, 2018). Retrievals uncertainty is not the only criteria for a good observing system.

Estimates stability …..

The Sentinel-2 A and B constellation, with its five-day re-look, can be integrated with other space-based sensors such as Landsat 8, to significantly improve the temporal resolution of datasets needed to monitor agricultural production (Battude et al., 2016; Claverie et al., 2018; Djamai et al., 2019). A temporally rich Landsat 8 - Sentinel-2 approach creates an opportunity to improve the monitoring of crop conditions and estimation of biomass and yield (Claverie et al., 2018; Defourny et al., 2019; Djamai et al., 2019; Wolanin et al., 2019).

The European Space Agency (ESA) sponsored the development of the Simplified Level 2 Prototype Processor (SL2P) for mapping these variables using Level 2A bottom of atmosphere reflectance (L2A) products derived from MSI data (Weiss and Baret, 2016). SL2P versions are implemented in ESA’s Sentinel Application Platform (SNAP) 9.0.0 (http://step.esa.int), used by the European Union SEN4CAP agricultural sustainability project ((http://esa-sen4cap .org/) and the open source LEAF-Toolbox (Fernandes et al., 2021) implemented in Google Earth Engine (GEE), and used by the Government of Canada Earth Observation for Cumulative Effects Monitoring Programme (Janzen et al., 2020).

Even so, this study does not evaluate the temporal stability of SL2P products as, prior to 2019, imagery over North America was not systematically processed to Level 2A surface reflectance products by ESA. The goals of this study are to:

1. Study sites and materials.
   1. In-situ reference measurements

In-situ reference measurements acquired within the National Ecological Observatory Network (NEON) across North America and Canada Centre for Remote Sensing (CCRS) - Natural Resources Canada’s Cumulative Effects study sites across Canada are used.

NEON sites included a wide range of vegetation types as defined by the National Land Cover Database (NLCD, [National Land Cover Database | U.S. Geological Survey (usgs.gov)](https://www.usgs.gov/centers/eros/science/national-land-cover-database)) classification: evergreen forest (EF), deciduous forest (DF), mixed forest (DF), cultivated crops (CC), emergent herbaceous wetlands (EHW), grassland herbaceous (GH), pasture hay (PH), sedge herbaceous (SH), shrub scrub (SS), woody wetlands (WW), and dwarf scrub (DS). While CCRS sites included EF, CF and MF.

Figure 1 shows the location of NEON and CCRS sites, as well as the dominant NLCD class for each site. More details are provided in Table xx of Appendix#.

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Figure 1: NEON and CCRS study sites.

For NEON sites, fraction of intercepted PAR (fIPAR), fCOVER, and LAI reference measures were derived from estimates of gap fraction obtained using digital hemispherical photography (DHP) 634 ESUs in 47 sites across North America (NEON, 2019[[1]](#footnote-1)). For each site, at least three 20 m by 20 m square ESUs were sampled bi-weekly from leaf-out to senescence for periods ranging from 3 to 6 years (Table ##). In each ESU, 12 co-located upward and downward looking DHP images were acquired with 4 m spacing in North-South and East-West transects through the plot centre using 36.3MPixel Nikon D810 or D800 cameras with a Nikon 16 mm Fisheye lens giving a 180◦ diagonal field of view (Meier et al. 2018[[2]](#footnote-2), Brown et al. 2020[[3]](#footnote-3)).

PAI was determined from upwards and downward images separately according to Miller (1967) approach, as the average of effective PAI estimates for 10 azimuthal intervals within zenith angle. The effective PAI for each azimuth angle was estimated as twice the negative logarithm of the gap fraction multiplied by the cosine of the zenith angle. fIPAR (fCOVER) was determined, from upwards and downward images, as one minus the mean gap fraction within ±5◦ of the solar zenith angle at 10:00 local solar time (±5◦ of nadir).

CCRS data are acquired for 133 ESUs in 11 forested sites. ESUs were located within the dominant land cover types at each site with replication where logistics permitted. For each ESU, seven co-located upward and downward DHP images were acquired every 5 m along two parallel transects spaced 15 m apart using 45.7 Mpixel Nikon D850 cameras with a Nikon 8 mm Fisheye lens giving a 180◦ FOV in all directions. DHPs for each ESU sampling date were visually quality controlled, contrast enhanced using ViewNXi software and masked to remove the field operator. CANEYE V6.45, using the same approach as GBOV, was used to derive PAI, fCOVER and fAPAR as well as the associated 1σ uncertainties for each upward or downward DHP image.

* 1. Satellite data

Landsat-8/OLI (L8) and Sentinel-2/MSI (S2) surface reflectance (SR) data are extracted from Google Earth Engine (GEE) collections LANDSAT/LC08/C02/T1\_L2 and COPERNICUS/S2\_SR\_HARMONIZED respectively. More details about data extraction are presented in section ###.

L8 is part of the Landsat Data Continuity Mission (Irons et al., 2012), launched by the European Space Agency on February 11, 2013. It has a sun-synchronous orbit at an altitude of ~705 km, with approximately 16-day revisit of the Earth and an equatorial overpass time of approximately 10:15 a.m. (descending node). It carries the Operational Land Imager (OLI) that has eight spectral bands at 30m spatial resolution covering the visible, the near infrared (NIR) and the shortwave-infrared (SWIR) spectral regions, and one 15m spatial resolution panchromatic band (Table ##). L8 surface reflectance data are estimated (atmospheric effects correction) using Landsat Surface Reflectance Code (LaSRC, Vermote et al., 2018[[4]](#footnote-4)).

S2 is a constellation of satellites, S2-A and S2-B, launched by the European Space Agency (ESA) on 23 June 2015 and 7 March 2017, respectively. They occupy the same sun-synchronous orbit at an altitude ~786 km but separated by 180°. Together, they provide better than 5-day revisit of the Earth's land surfaces with an equatorial overpass time at approximately 10:30 a.m. (descending node). S2-A and S2-B carry a virtually identical decametric resolution Multi-Spectral Imager (MSI) covering the visible, the near infrared (NIR) and the shortwave-infrared (SWIR) spectral regions (table ##). SR data are obtained by correcting atmospheric effects on to-of-atmosphere reflectance using the Sen2Cor processor (Version 2.4.0, Müller-Wilm [[5]](#footnote-5) et al., 2017).

Table ## L8-OLI bands (bands used by SL2P-CCRS are in bold)

|  |  |  |  |
| --- | --- | --- | --- |
| Band | Resolution | Central Wavelength (nm) | Description |
| B1 | 30 | 443 | Coastal / Aerosol |
| B2 | 30 | 482 | Blue |
| **B3** | **30** | **562** | **Green** |
| **B4** | **30** | **655** | **Red** |
| **B5** | **30** | **865** | **NIR** |
| **B6** | **30** | **1610** | **SWIR 1** |
| **B7** | **30** | **2200** | **SWIR 2** |
| B8 | 15 | 590 | Panchromatic |
| B9 | 30 | 1375 | Cirrus |

Table ## S2-MSI bands (bands used by SL2P-CCRS are in bold)

|  |  |  |  |
| --- | --- | --- | --- |
| Band | Resolution | Central Wavelength (nm) | Description |
| B1 | 60 m | 443 | Ultra Blue (Coastal and Aerosol) |
| B2 | 10 m | 490 | Blue |
| **B3** | **10 m** | **560** | **Green** |
| **B4** | **10 m** | **665** | **Red** |
| **B5** | **20 m** | **705** | **Visible and Near Infrared (VNIR)** |
| **B6** | **20 m** | **740** | **Visible and Near Infrared (VNIR)** |
| **B7** | **20 m** | **783** | **Visible and Near Infrared (VNIR)** |
| B8 | 10 m | 842 | Visible and Near Infrared (VNIR) |
| **B8a** | **20 m** | **865** | **Visible and Near Infrared (VNIR)** |
| B9 | 60 m | 940 | Water vapour |
| B10 | 60 m | 1375 | Cirrus |
| **B11** | **20 m** | **1610** | **Short Wave Infrared (SWIR)** |
| **B12** | **20 m** | **2190** | **Short Wave Infrared (SWIR)** |

1. Methodology
   1. Reference measures determination and filtering

Total LAI, fCOVER and fAPAR reference measures (RM) are determined by summing PAI, fCOVER and fIPAR quantities determined from downward and upward DHPs scaled by one minus the corresponding woody-to-total area ratios (Table xx, Fernandes et al. 2023[[6]](#footnote-6)).

The uncertainty of a RM value was estimated as the Euclidean sum of the understory and overstory 1σ uncertainties weighted by their proportion of the total RM. The 1σ uncertainty of overstory or understory components was estimated as the Euclidean sum of the 1σ uncertainties due to levelling error, sampling variability, the applied woody to total area ratio, ratio, and for LAI, a 0.025 1σ uncertainty due to clumping.

Table ##: woody-to-total area ratios for different NLCD classes

|  |  |  |
| --- | --- | --- |
| NLCD class | Overstory | Understory |
| EF | 0.16 (0.10) | 0.05 |
| DF | 0.24 (0.11) | 0.05 |
| MF | 0.18 (0.11) | 0.05 |
| Others | 0.10 (0.11) | 0.05 |

RM from NEON sites are filtered to reduce outliers (Figure ##, Appendix##). A moving window filtering approach was used. Considering a RM time-series for a given variable acquired on a specific ESU, each observation (with an uncertainty ) is compared to the 2 enveloping quantities and acquired within +/- 15-days (when they exists). Outlier flag is raised when three conditions are simultaneously satisfied:

With is an empirical threshold fixed for each vegetation variable.

In total, less than 1% of the total number of RM are detected as outliers (0.31% for LAI, 0.97% for fCOVER and 0.93% and fAPAR). More details are provided in Table ## in Appendix##).

* 1. Satellite-based vegetation variables estimates.

Canada Centre for remote Sensing version of the Simplified Level 2 Prototype Processor (SL2P-CCRS, Fernandes et al., 2024[[7]](#footnote-7)) implemented in Google Earth Engine within the Landscape Evolution And Forecasting (LEAF) Toolbox (Fernandes et al., 2021[[8]](#footnote-8)) is used to retrieve vegetation variables estimates from L8 and S2 SR data.

Briefly, SL2P is a collection of back-propagation artificial neural networks (ANN) trained using a globally representative set of simulations from a canopy radiative transfer model (RTM) based on joint distributions of leaf, canopy, soil, and acquisition geometry conditions. It is designed to estimate leaf area index (LAI), the fraction of absorbed photosynthetically active radiation (fAPAR), the fraction of vegetation cover (FCOVER), canopy chlorophyll content (CCC), and canopy water content (CWC) as well as their theoretical uncertainty from medium resolution multispectral satellite data. SL2P-CCRS defers from SL2P by (i) using land cover specific regressions instead of a single regression irrespective of land cover, (ii) using 4SAIL2 instead of SAILH to account for foliage clumping within shoots, and (iii) using Sobol model, instead of orthogonal sampling, for sampling canopy parameters from the joint distribution of input parameters.

SL2P-CCRS estimates of LAI, fCOVER and fAPAR associated with their quality control flags are retrieved from L8 and S2 data for the different available reference samples. Inputted bands are indicated in Table # (L8) and Table (S2). Valid SL2P-CCRS estimates for clear sky land pixels whose centroid fell within 30 m (20 m) radius for L8 (S2) (i.e. 3x3 pixels window) from the centre of each ESU and ± 7 days interval from the DHP acquisition date are extracted. Only satellite images with cloud cover less than 90% are considered. LaSRC and Sen2Cor cloud products are used for masking cloud from L8 and S2 images respectively. Additionally, S2 cloud probability product (S2cloudless, GEE collection 'COPERNICUS/S2\_CLOUD\_PROBABILITY’) is applied to improve the cloud mask for S2 data. Extracted SL2P-CCRS estimates from L8 and S2 are aggregated, using the median statistics, and associated as estimates for the different RMs.

* 1. Cross-validation

SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from L8 and S2 data are compared to RMs for ten different NLCD classes: EF, DF, MF, CC, EHW, GH, PH, SH, SS and WW (DS class was excluded from our analysis since ….). Thematic error metrics (Accuracy (A), Uncertainty (U), Precision (P)), the coefficient of determination (R2), and the uncertainty agreement ratio (UAR) of estimates obtained using SL2P-CCRS from L8 and S2 data, for the entire RMs, were computed (Eq: 1, 2, 3 and 4).

where, , (, ) are, respectively, the SL2P-CCRS estimate and RM for the ith of N comparisons (their corresponding average values), and , are, respectively, the relative and maximum target uncertainty requirement and I is the indicator function.

Additionally, as suggested by Global Leaf Area Index Product Validation Good Practices (Fernandes et al., 2014[[9]](#footnote-9)), thematic error metrics are plotted as a function of the RM value by considering a third order polynomial weighted least squares regressions fitted to quantities based on residuals between the mean of matching RM values and the corresponding SL2P-CCRS estimates as detailed in Fernandes et al. (2024).

* 1. Temporal stability.

Word Meteorological Organization defined the stability as “The change in bias over time” (WMO, 2022[[10]](#footnote-10)). It is a factor of uncertainties to demonstrate that the estimation error remains constant over the period, typically a decade or more.

In this study, the slope of annual estimates bias (annual bias slope, ABS) was computed as a proxy of the stability. Annual bias (AB) values are computed for years with at least 5 RMs/estimates matchups. Then, linear fit regressor is considered to estimate the slope (S) when at least 5 (4 for L8) estimates of AB are a4vailable. The mean and the standard deviation of AB values (AB-AVG and AB-STD, respectively), as well as the 95% Confidence Interval of the slope (CI) are computed to assess the robustness and for the analysis of the stability proxy.

ABS values are computed for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from both L8 and S2 data, considering (i) all sites merged together, and (ii) at site basis (e.i. for each single site); for sites with more than one NLCD class (e.g. ABBY site, Table ##), each class is considered separately.

* 1. SL2P-CCRS L8/S2 estimates comparison.

SL2P-CCRS vegetation variables estimates from L8 are directly compared to the corresponding estimates obtained from S2 acquired within +/- 1 day maximum. Thematic error metrics (A, P, U) and R2 are used compare SL2P-CCRS estimates obtained from different sensor for different NLCD classes.

1. Results
   1. Cross-validation

Scatter plots of LAI, fCOVER and fAPAR estimates obtained using SL2P-CCRS from L8 and S2 against the corresponding RMs are showed in Figure 2. Table ## presents the number of matchups and variation range of RM used for the validation of estimates obtained from L8 and S2 data for each NLCD class.

A total of 6313 matching was found between SL2P-CCRS estimates obtained from L8 data and reference samples (Figure 2a), compared to #4935 matching when using S2 (Figure 2b). LAI, fCOVER and fAPAR RM ranges from 0 to 5.96, from 0 to 0.96, and from 0 93 for samples corresponding to L8 estimates, and from 0 to 6.87, from 0 to 0.99, and from 0 to 0.95 for samples corresponding to L8 estimates.

Figures 2.a and 2.b. indicates that despite a relatively linear relationships between estimates and RM (R2 ~0.75), SL2P-CCRS underestimate LAI whether using L8 (A=-0.52) or S2 (A=-0.45) data. This explains the high uncertainty (1.30 for L8 and 1.24 for S2) and the low UAR (0.09 for L8 and 0.12 for S2) of estimates. This is an expected result since SL2P-CCRS is not properly accounting for clumping. Conversely, fCOVER estimates are ~unbiased whatever the used sensor, and ~equal uncertainty (~0.15), R2 (0.75) and UAR (0.35) quantities are obtained for estimates from L8 and S2. SL2P-CCRS fAPAR estimates are slightly underestimated (A=-0.04). But, again, ~equal uncertainty (0.17), R2 (~0.71) and UAR (0.32) qualities are obtained when using L8 or S2 data.

Considering cover type specific statistics, computed with unbalanced sample sizes, SL2P-CCRS estimates are underestimated irrespective to the used sensor or the variable for woody wetlands, evergreen forest, deciduous forest, and mixed forest: from-1.87 to -0.78 for LAI, from -0.12 to -0.01 for fCOVER, and from -0.19 to -0.08 for fAPAR. While estimates are overestimated for the other croplands: from 0.17 to 1.16 for LAI, from 0.06 to 0.33 for fCOVER, and from 0.05 to 0.31 for fAPAR. The underestimation is higher for woody wetlands, and the overestimation is higher for sedge herbaceous.

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Description automatically generated with medium confidenceFigure 2: Scatter plots of ESU SL2P-CCRS estimates versus matching RM for each variable together with population validation metrics. Dashed lines bound target user requirement around solid 1:1 line.

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Figure 3: Validation metrics per NLCD class type for LAI, fCOVER and fAPAR SL2P-CCRS estimates from L8 and S2 data against RMs.

Table ##: sample size and variation range of RM data used for SL2P-CCRS estimates from L8 data.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | fCOVER | | | fAPAR | | |
| **NLCD** | **MIN** | **MAX** | **N** | **MIN** | **MAX** | **N** | **MIN** | **MAX** | **N** |
| EHW | 0.58 | 2.02 | 35 | 0.13 | 0.58 | 35 | 0.16 | 0.60 | 35 |
| SH | 0.71 | 1.88 | 67 | 0.22 | 0.61 | 67 | 0.21 | 0.60 | 67 |
| CC | 0.11 | 4.13 | 226 | 0.00 | 0.84 | 226 | 0.03 | 0.84 | 226 |
| PH | 0.57 | 3.81 | 374 | 0.04 | 0.84 | 374 | 0.03 | 0.83 | 374 |
| SS | 0.20 | 5.96 | 570 | 0.00 | 0.96 | 570 | 0.00 | 0.93 | 570 |
| GH | 0.10 | 5.71 | 1095 | 0.00 | 0.94 | 1095 | 0.01 | 0.91 | 1095 |
| WW | 0.57 | 5.43 | 137 | 0.19 | 0.88 | 137 | 0.18 | 0.85 | 137 |
| MF | 0.51 | 4.70 | 305 | 0.18 | 0.89 | 305 | 0.17 | 0.86 | 305 |
| DF | 0.04 | 5.67 | 1716 | 0.03 | 0.95 | 1716 | 0.04 | 0.92 | 1716 |
| EF | 0.01 | 4.48 | 1788 | 0.01 | 0.87 | 1788 | 0.02 | 0.85 | 1788 |
| All | 0.01 | 5.96 | 6313 | 0.00 | 0.96 | 6313 | 0.00 | 0.93 | 6313 |

Table ##: sample size and variation range of RM data used for SL2P-CCRS estimates from S2 data.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | fCOVER | | | fAPAR | | |
| **NLCD** | **MIN** | **MAX** | **N** | **MIN** | **MAX** | **N** | **MIN** | **MAX** | **N** |
| EHW | 0.16 | 1.88 | 40 | 0.03 | 0.41 | 40 | 0.04 | 0.41 | 40 |
| SH | 0.74 | 2.37 | 79 | 0.18 | 0.64 | 79 | 0.19 | 0.62 | 79 |
| CC | 0.01 | 4.03 | 163 | 0.00 | 0.90 | 163 | 0.01 | 0.88 | 163 |
| PH | 0.15 | 4.86 | 319 | 0.06 | 0.88 | 319 | 0.08 | 0.86 | 319 |
| SS | 0.00 | 6.08 | 420 | 0.00 | 0.92 | 420 | 0.00 | 0.90 | 420 |
| GH | 0.00 | 4.95 | 747 | 0.00 | 0.90 | 747 | 0.00 | 0.85 | 747 |
| WW | 0.63 | 5.31 | 84 | 0.17 | 0.89 | 84 | 0.18 | 0.88 | 84 |
| MF | 0.29 | 5.22 | 195 | 0.03 | 0.92 | 195 | 0.01 | 0.89 | 195 |
| DF | 0.08 | 6.87 | 1330 | 0.01 | 0.99 | 1330 | 0.04 | 0.95 | 1330 |
| EF | 0.16 | 5.00 | 1558 | 0.05 | 0.87 | 1558 | 0.06 | 0.84 | 1558 |
| All | 0.00 | 6.87 | 4935 | 0.00 | 0.99 | 4935 | 0.00 | 0.95 | 4935 |

* 1. Accuracy, precision, and uncertainty as a function of RM value (APU curves)

Figure 4 shows APU curves for LAI, fCOVER and fAPAR SL2P-CCRS estimates from L8 and S2 data, as well as histograms of data samples used to fit APU models. The increased sample density of data for the different variable’s levels (in average 800 S2 and 600 L8 samples used for LAI, 600 S2 and 400 L8 samples used for fCOVER and fAPAR) explains the narrow confidence interval of APU models obtained for each variable. Wider confidence intervals are for the highest variables’ levels (i.e. LAI>6, fCOVER>0.9, and fAPAR>0.9) due to the lower sample density (i.e. ~200 samples for LAI, ~100 samples for fCOVER and ~180 samples for fAPAR, regardless the sensor).

APU curves associated to estimates from L8 data compares well with the corresponding curves obtained for estimates from S2 data, regardless the vegetation variable.

LAI estimates uncertainty ~linearly increases from ~0 for LAI ~0 to ~3 for LAI~7; it satisfies GCOS requirements only for LAI<3. In contrast, the accuracy ~linearly decreases from ~0 for LAI~0 to ~-3 for LAI~7. Whereas the precision remains ~stable and lower than 1 for all ranges. The accuracy and the precision of estimates from L8 are found slightly lower than the corresponding quantities from S2, in contrast to the uncertainty which is slightly higher for L8.

For fCOVER, the accuracy and the uncertainty simultaneously increase from ~0.1 to ~0.15 for the range 0 - 0.2, then decrease to ~-0.1 (accuracy) and ~0.1 (uncertainty) for the range 0.2-0.8, and finally increase to ~-0.5 (accuracy) and 0.2 (uncertainty) for the range 0.8-1. The precision remains ~ stable (~0.1) for the entire range. Target uncertainty requirements are only satisfied for fCOVER levels from 0.5 to 0.9.

For fAPAR, the accuracy decreases from ~ 0.2 for fAPAR~0 to ~-0.2 for fAPAR~1. While the uncertainty decreases from ~0.2 to ~0.1 for the range 0 - 0.5, then it increases back from ~0.1 to ~0.2 for the range 0.5 - 1. Whoever, the precision, as for LAI and fAPAR, remains ~stable for the entire range.

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Description automatically generatedFigure 4: APU curves and the corresponding 95% confidence intervals (dashed contours) for LAI, fCOVER and fAPAR estimates obtained using SL2P-CCRS from S2 and L8 data. Dashed grey lines bound target user requirements.

* 1. Temporal stability of vegetation variable estimates

Figure ## shows the variation of AB between LAI estimates from L8 (S2) and RMs between 2014 (2019) and 2022. AB values are computed with at least ~200 samples/year for L8 and at least 700 samples/year for S2.

Results indicates that LAI estimates from L8 are quite stable during about one decade of estimates (9-years, ABS ~-0.03 units/year). AB values range between ~-1 and -0.40 units with an average of -0.60 and a standard deviation of 0.17. Results for LAI estimates from S2 are not concussive since covers a shorter period of time (4-years). Nerveless, AB values for LAI estimates from S2 data fit well with corresponding values obtained for estimates from L8 data during the overlapping period (from 2019 to 2022).

Similar results are obtained for fCOVER and fAPAR estimates (not shown to avoid complexity). Notably, the stability of estimates obtained from L8 (ABS (CI) ~0 (<0.01)) for both, and the unconclusive of ABS values obtained for estimates from S2.

The stability of SL2PCCRS estimates from L8 and S2 data is further investigated at sites basis. However, only ABS values and the associated confidence intervals are reported to avoid complexity. Figure ## shows scatter plots of ABS values compared to AB-AVG for LAI, fCOVER and fAPAR over 42 NEON sites with NLCD classes, the size of circles is proportional to the site mean RM for a given variable. The obtained ABS values range from ~0.17 to 0.08 (average -0.01 and std ~0.06) for LAI [CI mean ~0.13 and std ~0.11], and from -0.02 to 0.02 (average 0 and std 0.01) for fCOVER and fAPAR [CI mean ~0.02 and std ~0.01].

Despite the shorter covered period (unconclusive results), comparable ABS values are generally observed for estimates from S2 data (Figure ##), but with larger CIs. In fact, ABS values ranges between -0.18 and 0.25 (average 0.02 and standard deviation 0.09) for LAI [CI mean ~0.26 and std ~0.13], and from -0.03 to 0.03 (average ~0 and standard deviation ~0.01) for fCOVER and fAPAR [CI mean ~0.05 and std ~0.03].

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Figure ##: AB profile with ABS value indicated for SL2PCCRS estimates of LAI obtained from L2 and S2 data for all sites merged.

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Figure ##: Scatter plots of ABS vs. AB-AVG for SL2PCCRS estimates of LAI, fCOVER and fAPAR obtained from L8 data. x/y error bars: CI / AB-STD, size: RM-AVG, color: NLCD class.

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Figure ##: Scatter plots of ABS vs. AB-AVG for SL2PCCRS estimates of LAI, fCOVER and fAPAR obtained from S2 data. x/y error bars: CI / AB-STD, size: RM-AVG, color: NLCD class.

* 1. Direct comparison of estimates obtained from L8 to estimates from S2

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Appendix:

1. CCRS and NEON site used for the study.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Site** | **Network** | **#ESUs** | **Start Date** | **End Date** | **#sample** | **NLCD (#sample)** |
| Peace River | CCRS | 3 | 2019-08-12 | 2019-08-12 | 3 | DF (3) |
| YellowKnife | 3 | 2019-08-11 | 2019-08-12 | 3 | EF (3) |
| Merbleue | 3 | 2019-09-18 | 2019-09-18 | 3 | EF (2), DF (1) |
| Hay River | 28 | 2019-09-05 | 2019-09-07 | 28 | EF (27), MF (1) |
| Geraldton | 3 | 2020-07-21 | 2020-07-21 | 3 | EF (2), DF (1) |
| NovaScotia | 3 | 2021-08-26 | 2021-08-27 | 3 | EF (2), DF (1) |
| Turkey Point | 3 | 2019-06-27 | 2019-06-27 | 3 | EF (2), DF (1) |
| Vancouver Island | 3 | 2019-08-09 | 2019-08-10 | 3 | EF (3) |
| MtPolley | 3 | 2019-08-14 | 2019-08-15 | 3 | MF (2), EF (1) |
| Labrador | 12 | 2019-07-24 | 2019-07-31 | 12 | MF (6), EF (6) |
| STER | NEON | 19 | 2014-04-01 | 2022-09-08 | 357 | CC (357) |
| KONA | 24 | 2017-06-22 | 2022-10-27 | 221 | CC (221) |
| TREE | 23 | 2015-07-08 | 2022-06-21 | 238 | DF (145), MF (79), WW (11), EF (3) |
| UKFS | 24 | 2016-04-06 | 2022-10-25 | 326 | DF (268), EF (55), GH (3) |
| BART | 27 | 2016-04-14 | 2022-11-17 | 373 | DF (234), MF (128), EF (11) |
| SERC | 25 | 2017-06-16 | 2022-09-12 | 362 | DF (356), CC (6) |
| SCBI | 27 | 2015-04-29 | 2022-09-26 | 410 | DF (402), PH (8) |
| STEI | 23 | 2014-05-08 | 2022-10-18 | 265 | DF (259), MF (3), WW(3) |
| BLAN | 22 | 2015-09-12 | 2022-06-21 | 369 | DF (126), SS (118), CC (115), PH (10) |
| CLBJ | 25 | 2016-03-23 | 2022-11-01 | 348 | DF (328), GH (20) |
| ORNL | 31 | 2016-03-09 | 2022-11-27 | 437 | DF (416), EF (12), PH (9) |
| LENO | 23 | 2014-06-06 | 2022-09-26 | 307 | DF (193), WW (114) |
| GRSM | 23 | 2017-08-14 | 2022-10-04 | 323 | DF (319), EF (4) |
| MLBS | 23 | 2016-06-08 | 2022-12-03 | 214 | DF (214) |
| BONA | 25 | 2014-06-04 | 2022-10-25 | 181 | DF (93), EF (77), SS (6), MF (3), WW (2) |
| DELA | 26 | 2015-04-19 | 2022-10-03 | 332 | DF (294), WW (34), EF (4) |
| HEAL | 23 | 2017-07-17 | 2022-08-22 | 176 | DS (160), SS (15), EF (1) |
| BARR | 23 | 2018-04-26 | 2022-08-23 | 79 | EHW (64), SH (15) |
| TEAK | 20 | 2013-04-17 | 2022-08-10 | 92 | EF (91), SS (1) |
| JERC | 26 | 2015-07-28 | 2022-12-29 | 378 | EF (364), DF (7), MF (4), CC (3) |
| SOAP | 23 | 2018-07-30 | 2021-09-22 | 152 | EF (150), SS (2) |
| ABBY | 18 | 2016-11-01 | 2022-11-24 | 211 | EF (139), GH (68), SS (3), MF (1) |
| YELL | 17 | 2018-06-12 | 2022-11-01 | 83 | EF (72), SS (10), GH (1) |
| GUAN | 24 | 2019-06-13 | 2022-09-27 | 518 | EF (518) |
| SJER | 23 | 2014-05-16 | 2022-10-12 | 342 | EF (207), DF (101), GH (30), SS (4) |
| RMNP | 25 | 2016-07-06 | 2022-09-12 | 197 | EF (82), DF (58), MF (57) |
| PUUM | 23 | 2013-06-11 | 2022-08-04 | 320 | EF (320) |
| OSBS | 34 | 2017-08-04 | 2022-10-25 | 474 | EF (435), WW (22), DF (7), MF (6), EHW (4) |
| WREF | 27 | 2018-04-10 | 2022-11-01 | 176 | EF (176) |
| DEJU | 23 | 2016-08-25 | 2022-07-05 | 170 | EF (160), SS (8), WW (2) |
| TALL | 23 | 2016-03-16 | 2022-10-27 | 411 | EF (390), DF (12), MF (9) |
| KONZ | 24 | 2016-05-10 | 2022-10-17 | 352 | GH (348), DF (4) |
| NOGP | 23 | 2015-07-14 | 2022-09-19 | 274 | GH (274) |
| NIWO | 24 | 2017-06-19 | 2022-10-19 | 201 | GH (188), EF (13) |
| DCFS | 23 | 2014-03-26 | 2022-10-26 | 247 | GH (247) |
| CPER | 23 | 2014-05-08 | 2022-10-19 | 451 | GH (451) |
| WOOD | 27 | 2014-05-01 | 2022-10-24 | 372 | GH (361), EHW (11) |
| HARV | 21 | 2014-05-20 | 2022-07-12 | 378 | MF (244), EF (126), DF (6), WW (2) |
| UNDE | 27 | 2016-04-15 | 2022-12-29 | 286 | MF (105), WW (100), DF (81) |
| LAJA | 4 | 2013-02-11 | 2022-09-21 | 456 | PH (455), EF (1) |
| DSNY | 24 | 2017-07-10 | 2022-08-15 | 488 | PH (452), WW (36) |
| TOOL | 22 | 2021-07-15 | 2021-07-22 | 133 | SH(111), DS (20), SS (2) |
| SRER | 23 | 2016-04-27 | 2022-10-24 | 339 | SS (339) |
| JORN | 23 | 2015-06-10 | 2022-11-01 | 335 | SS (335) |
| OAES | 20 | 2016-03-21 | 2022-11-15 | 323 | SS (213), GH (110) |
| ONAQ | 23 | 2014-05-22 | 2022-09-13 | 350 | SS (337), EF (13) |
| MOAB | 23 | 2015-05-13 | 2022-11-01 | 314 | SS (311), EF (3) |
| **Total** |  |  |  |  | **14205** |  |

1. Reference measures filtering.

A graph of data showing the number of data

Description automatically generated with medium confidence

Figure ##: example of outliers detected on RM time series acquired on NEON site ####

Table ##: number and fraction of outliers detected for each variable and NEON site compared to the total sample size.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | fCOVER | | | fAPAR | | |
| **Land Cover** | **#samples** | **#Filtered** | **Fraction (%)** | **#samples** | **#Filtered** | **Fraction (%)** | **#samples** | **#Filtered** | **Fraction (%)** |
| evergreen Forest | 3427 | 3 | 0.09 | 3427 | 30 | 0.88 | 3427 | 16 | 0.47 |
| grassland Herbaceous | 2101 | 1 | 0.05 | 2101 | 4 | 0.19 | 2101 | 3 | 0.14 |
| shrub Scrub | 1704 | 0 | 0 | 1704 | 1 | 0.06 | 1704 | 1 | 0.06 |
| mixed Forest | 639 | 1 | 0.16 | 639 | 1 | 0.16 | 639 | 1 | 0.16 |
| sedge Herbaceous | 126 | 0 | 0 | 126 | 0 | 0 | 126 | 0 | 0 |
| emergent Herbaceous Wetlands | 79 | 0 | 0 | 79 | 0 | 0 | 79 | 0 | 0 |
| deciduous Forest | 3923 | 19 | 0.48 | 3923 | 28 | 0.71 | 3923 | 31 | 0.79 |
| pasture Hay | 934 | 16 | 1.71 | 934 | 55 | 5.89 | 934 | 48 | 5.14 |
| cultivated Crops | 702 | 2 | 0.28 | 702 | 16 | 2.28 | 702 | 16 | 2.28 |
| woody Wetlands | 326 | 2 | 0.61 | 326 | 2 | 0.61 | 326 | 2 | 0.61 |
| dwarf Scrub | 180 | 0 | 0 | 180 | 0 | 0 | 180 | 0 | 0 |
| **total** | **14141** | **44** | **0.31** | **14141** | **137** | **0.97** | **14141** | **118** | **0.83** |

A diagram of a graph

Description automatically generated with medium confidence

A diagram of a graph

Description automatically generated with medium confidence

BARR, TOOL, HEAL??

A diagram of a graph

Description automatically generated with medium confidence

A diagram of different colored dots

Description automatically generated with medium confidenceA diagram of a graph

Description automatically generated with medium confidenceA diagram of a graph

Description automatically generated with medium confidenceA diagram of different colored lines

Description automatically generated with medium confidenceA diagram of a graph

Description automatically generated with medium confidenceA diagram of a number of colored dots

Description automatically generated with medium confidenceA diagram of different colored dots

Description automatically generated with medium confidenceA diagram of a graph

Description automatically generated with medium confidence

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