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

1. Introduction

Systematic <=100m resolution global mapping of vegetation biophysical variables, including the leaf area index (LAI), the fraction of vegetation cover (fCOVER) and the fraction of absorbed photosynthetically active radiation (fAPAR), is required to support climate adaptation, crop management, biodiversity monitoring, and ecosystem assessments (WMO, 2022; GEOGLAM, 2023; GEOBON, 2023). At present, satellite climate data records (SDRs) of multispectral imagery are primary inputs for globally applicable algorithms capable of mapping these variables (CEOS, 2022). Such records are only globally available in a free and open manner from the Sentinel-2 (S2) and Landsat imagers (xx,xx). LAI, fCOVER, and fAPAR products derived from these SDRs have been validated at a significant number of locations and time periods representative of global conditions (xx,xx,xx), or Comittee of Earth Observig Systems Stage 3 (CEOS, xx). However, validation of inter-annual time series using the available fiducial reference measurements (RMs) over a global network of sites and time periods, corresponding CEOS Stage 4, has not been achieved due to the limited temporal overlap of SDRs and RMs.

Stage 4 validation includes quantification of the temporal stability of product uncertainty, defined as the change in bias at interannual time scales. Stability is essential for quantifying trends and anomalies in essential climate variables and physical quantities or indicators derived through their integration into models. Currently, only the National Ecological Observatory Network (NEON, Kao et al, 2012) across North America, with measurements beginning in 2013, offers interannual RMs for period >=5years. This limits the scope of Stage 4 validation to products derived from Landsat 8/9 (LS) or S2 images. Here, products from globally applicable algorithms relying on LS imagery was considered as consistently processed S2 SDRs were unavailable prior to 2020 for the NEON sites at the time our study was conducted.

Products derived using the SL2P-CCRS algorithm were validated in this study for three reasons. i. because Stage 3 validation using S2 SDRs indicates it has reasonable thematic performance with an uncertainty less than 0.15 for fAPAR, and less than 0.86 for LAI (Fernandes et al., 2024).

ii. it already has been generated at sub-continental scale (xx,xx) and can be generated efficiently at global basis in a free and open manner.

iii. local (Stage 1,2) validation studies suggest that the uncertainty of fAPAR and LAI estimates using algorithms similar to SL2P-CCRS may increase when using L8/9 versus S2 SDRs (Djamai et al., 2019).

Both NEON and Canada Centre for Remote Sensing (CCRS, Fernandes et al. 2023) measurements were used for validation to facilitate comparison with previous Stage 3 S2 validation. However, only NEON sites had sufficient inter-annual sampling required to quantify stability.

The goal of our study was to answer for three questions:

1. What is the accuracy (A), precision (P), and uncertainty (U) of fCOVER, fAPAR and LAI estimates obtained using SL2P-CCRS from LS SDRs (SL2P-CCRS/LS) in comparison to the corresponding estimates obtained using SL2P-CCRS from S2 SDRs (SL2P-CCRS/S2)?
2. What is the consistency of SL2P-CCRS/LS retrievals of fCOVER, fAPAR and LAI compared to the corresponding SL2P-CCRS/S2 retrievals?
3. What is stability of annual aggregated fCOVER, fAPAR and LAI estimates as a function of land cover and magnitude of the variable considered.

We hypothesize that SL2P-CCRS/LS products will result in significantly greater uncertainty compared to SL2P-CCRS/S2 due to increased bias due to modelling and local validation studies (xx). We also hypothesize that SL2P-CCRS/LS and SL2P-CCRS/S2 will be linearly related for a given land cover class but not along the 1:1 line due to the increased expected bias for LS SDR inputs.

We are unable to hypothesize regarding the stability of products due to the absence of previous modelling or empirical studies. However, we do hypothesize that the observed stability will be less than the precision of our ability to estimate stability due to the limited annual overlap between LS SDRs and NEON RMs.

Our study is novel in that (1) it is first study to provide a Stage 4 validation of L8/9 and indeed a Stage 3 validation using a free and open globally applicable algorithm, (2) it propose a new approach to quantifying stability relyint on a new extended NEON FRM dataset, (3) and it present a basis for the first medium resolution ECV CDR when the L8/9 recahes temporal extent for relevance in climate studies.

Impact

* A, P, U and bias correction results for L8/9 for areas represented by NEON sites
* Uncertainty of annual trends and anomalies of ECVs derived from L8/9 SDRs
* Error budget for combining products derived from multiple SDRs allowing for increased temporal sampling and data continuity
* Good practice for stability assessments

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

RMs were acquired at 47 NEON site and 10 CCRS sites across Noth America (Figure 1), including sites used for previous S2 validation studies (Brown et al. 2021, Fernandes et al. 2023, Fernandes et al. 2024) with details regarding site names, locations, land cover and in-situ sampling provided in Table 1 and Appendix A. NEON sites included a wide range of National Land Cover Database (NLCD, <https://www.usgs.gov/centers/eros/science/national-land-cover-database>) classes indicated in Table 1. While CCRS sites only included three NLCD classes: EF, DF and MF.

Table 1: NLCD classes

|  |  |  |
| --- | --- | --- |
| **NLCD class** | **Abbreviate** | **Forestland class** |
| Evergreen forest | EF | x |
| Deciduous forest | DF | x |
| Mixed forest | MF | x |
| Cultivated crops | CC |  |
| Emergent herbaceous wetlands | EHW |  |
| Grassland herbaceous | GH |  |
| Pasture hay | PH |  |
| Sedge herbaceous | SH |  |
| Shrub scrub | SS |  |
| Woody wetlands | WW | x |
| Dwarf scrub | DS |  |

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Figure 1. NEON and CCRS sites, as well as the dominant NLCD class for each site.

RMs for LAI, fCOVER and fAPAR spanning 2013 to 2022, previously used in Brown et al. 2021, Fernandes et al. 2023, Fernandes et al. 2024 were supplemented with additional RMs for NEON sites processed by the authors using the same in-situ measurement and post-processing methods for previously published measurements at each site. These approaches are only briefly described here as they are given in greater detail in Fernandes et al. 2024.

1. Measurements were conducted at elementary sampling units (ESUs) with a typical spatial footprint on the order of 25 m radius for 20 m tall canopies with a proportionate change in radius with changing canopy height.
2. CCRS ESUs were surveyed once during the peak growing season 2019 or 2019. While, for NEON sites, a minimum of three plots ESUs were surveyed bi-weekly from leaf-out to senescence.
3. In-situ measurements corresponded to co-located upward and downward looking digital hemispherical photographs (DHP) at between 12-14 locations along either parallel transects (CCRS) or a grid pattern (NEON) in the ESU.
4. Measurements were visually quality controlled and processed using CANEYEV.4.65 (https://www6.paca. inrae.fr/can-eye/Download/ accessed on September 1, 2023, CCRS) or HEMIPY (Brown et al., 2023, NEON) to give overstory and understory fIPAR, fCANOPY, PAI for the plot and for individual images.
5. Total LAI, fCOVER and fAPAR were quantified as in Fernandes et al. 2024 using empirical woody-to-total area ratios given in Table 2.
6. The one standard deviation precision error of each measurement was modelled using the RMs protocol that includes with-site variability, measurement errors and post-processing error except for bias in correction for non-randomness in foliage locaton (clumping). The clumping bias was expected to be <5% on average and not exceeding 10% based on studies relying on numerical simulations (xx). The bias would be expected to vary seasonally but would likely be constant inter-annually as NEON ESUs are controlled for land cover disturbance.

Table 2: woody-to-total area ratios and their uncertainties used for overstory and understory DHP acquisitions.

|  |  |  |
| --- | --- | --- |
| NLCD (site) | Overstory | Understory |
| DF | 0.24 (0.11) | 0.05 |
| MF | 0.18 (0.11) | 0.05 |
| EF (ABBY) | 0.70 (0.19) | 0.05 |
| EF (WREF) | 0.75 (0.19) | 0.05 |
| EF (PUUM) | 0.65 (0.19) | 0.05 |
| EF (TEAK) | 0.60 (0.19) | 0.05 |
| EF (others) | 0.16 (0.10) | 0.05 |
| Others | 0.10 | 0.05 |

* 1. Satellite data

Surface reflectance data are extracted from Google Earth Engine (GEE) collections LANDSAT/LC08/C02/T1\_L2 (L8), LANDSAT/LC09/C02/T1\_L2 (L9), and collection COPERNICUS/S2\_SR\_HARMONIZED (S2). More details about data extraction are presented in section 3.2.

Together, L8 and L9 provide revisit periods ranging between 2 and 8 days over our study sites with an overpass time at approximately 10:15 a.m. They carry virtual identical Operational Land Imager (OLI) with eight spectral bands at 30m spatial resolution and one 15m spatial resolution panchromatic band (Table 3). LS surface reflectance data are estimated using Landsat Surface Reflectance Code (LaSRC, Vermote et al., 2018).

Together, S2-A and S2-B provide revisit periods ranging between 2 and 5 days over our study sites with an approximate overpass time at 10:30 a.m. They carry a virtually identical Multi-Spectral Imager (MSI) with 13 spectral bands at spatial resolutions ranging between 10m and 60m (Table 4). S2 SR data are obtained by correcting atmospheric effects on to-of-atmosphere reflectance using the Sen2Cor processor (Version 2.4.0, Müller-Wilm et al., 2017).

The geolocation uncertainty of LS and S2 SR products are less than 12.5 m (Storey et al., 2014, Gascon et al., 2017), while the radiometric uncertainty is less than 5% for flat areas (Markham et al., 2014; Morfitt et al., 2015; Djamai and Fernandes, 2018; Doxani et al., 2018).

Table 3: L8-OLI bands (SL2P-CCRS input bands 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** | **Near-Infrared** |
| **B6** | **30** | **1610** | **Short Wave Infrared** |
| **B7** | **30** | **2200** | **Short Wave Infrared** |
| B8 | 15 | 590 | Panchromatic |
| B9 | 30 | 1375 | Cirrus |

Table 4: S2-MSI bands (SL2P-CCRS input bands are in bold)

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

1. Methodology
   1. Reference measures determination and filtering

RMs from NEON sites are filtered to reduce outliers that could be due overexposure, colour balance issues, or variable illumination (Figure 1, Appendix B).

A moving window filtering approach was used. Considering RMs 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 RMs are detected as outliers (0.31% for LAI, 0.97% for fCOVER and 0.93% and fAPAR). More details are provided in Table 1 in Appendix B).

* 1. Satellite-based vegetation variables estimates.

SL2P-CCRS/LS and SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR associated with their quality control flags are retrieved for the different RMs. Inputted bands are indicated in Table 3 (L8) and Table 4 (S2). Valid estimates for clear sky land pixels whose centroid fell within 30 m (20 m) radius for LS (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 to screen out low quality images. LaSRC and Sen2Cor cloud products are used to mask pixels neither bare nor vegetated (cloud, cloud shadow, water, snow, ….) from LS and S2 images respectively. S2 cloud probability product (S2cloudless, GEE collection 'COPERNICUS/S2\_CLOUD\_PROBABILITY’) was also considered to improve the cloud mask for S2 data. Extracted SL2P-CCRS estimates from LS and S2 are aggregated, using the median statistics, and associated as estimates for the different RMs.

* 1. Cross-validation

SL2P-CCRS/LS and SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR are compared to RMs for ten different NLCD classes. Dwarf scrub was excluded from our analysis due to the significant impact of background color on estimates (very sparce vegetation). RMs for BARR, TOOL and DEJU sites (showing a class underestimation compared to estimates, Figure 1, Appendix C), are adjusted by adding the bias.

The accuracy (A), the uncertainty (U), the precision (P), the coefficient of determination (R2), and the uncertainty agreement ratio (UAR) of SL2P-CCRS/L8 and SL2P-CCRS/S2 estimates were computed for the entire population (RMs) as:

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), thematic error metrics (A, P, U) are plotted as a function of the RMs value by considering a third order polynomial weighted least squares regressions fitted to quantities based on residuals between the mean of matching RMs values and the corresponding SL2P-CCRS/LS and SL2P-CCRS/S2 estimates as detailed in Fernandes et al. (2024).

* 1. Intercomparison

SL2P-CCRS/L8 estimates of LAI, fCOVER and fAPAR and the corresponding SL2P-CCRS/S2 estimates acquired within +/-1 day during the entire overlapping period (from 2018 to 2023) are extracted for all NEON and CCRS sites, and processed as described in section 3.2. Multi-source estimates are directly compared using density contour plots and R2, A, P and U statistics for the different NLCD classes.

* 1. Temporal stability.

Stability (S) was quantified for LAI, fCOVER and fAPAR obtained from both LS and S2 data, considering (i) all sites merged, and (ii) at site basis (e.i. for each single site); for sites with more than one NLCD class (e.g. ABBY site, Table 1 in Appendix A), each class is considered separately.

For each site, S was estimates as the slope of ordinary least squares regression of estimated annual bias (AB). AB is estimated for sites with an intra-annual sampling frequency of at least 5 bi-weekly dates per year. Only S estimates based on at least 5 LS or 4 S2 AB samples were retained to minimize the impact of sample size on the precision of the bias estimate. 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) was used to quantify the precision of the stability estimate.

1. Results
   1. Cross-validation

Figure 2 present scatter plots of SL2P-CCRS/LS estimates of LAI, fCOVER and fAPAR against RMs together with population validation metrics. Similar scatter plots obtained using SL2P-CCRS/S2 is presented in Figure 1 (Appendix C).

A total of 6641 matchups were found between SL2P-CCRS/L8 estimates and RMs. RMs ranges from 0.01 to 5.96 for LAI, from 0 to 0.96 for fCOVER, and from 0 to 0.93 for fAPAR (Figure 3 and Table 1 in Appendix 3).

Figures 2 indicates that despite the linear relationships between estimates and RMs (R2 ~0.80), SL2P-CCRS/L8 underestimate LAI (A=-0.42, U=1.14). This explains the low UAR (~0.10) obtained for LAI estimates. Conversely, fCOVER and fAPAR estimates are ~unbiased, with equal uncertainty (~0.13) and R2 (~80) compared to RMs, and UAR=<40%.

In general, validation statistics obtained for estimates from SL2P-CCRS/L8 are comparable to validation statistics obtained for estimates from SL2P-CCRS/S2 using ~the same RMs, except for LAI accuracy and LAI uncertainty where slightly better results are obtained using S2 (A=-0.32, U= 1.00).

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Figure 2: Scatter plots of SL2P-CCRS/L8 estimates of LAI, fCOVER and fAPAR versus matching RMs together with population validation metrics. Dashed lines bound target user requirement around solid 1:1 line.

Figure 3 presents validation metrics as well as the sample size and the variation range of RMs for each class. Similarly, it indicates that comparable class specific statistics are generally obtained for SL2P-CCRS/L8 and SL2P-CCRS/S2, mainly for A and U statistics. SL2P-CCRS estimates are underestimated irrespective to the sensor (L8 or S2) and the vegetation 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. The underestimation is always higher for woody wetlands. While estimates are overestimated for the other classes: from 0 to 0.46 for LAI, from 0.01 to 0.12 for fCOVER, and from 0.01 to 0.08 for fAPAR.

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Figure 3: Class specific validation metrics for SL2P-CCRS/L8 and SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR against RMs together with used samples size (histograms) and RMs variation range (bars, intermediate point corresponds to the median value).

Figure 4 shows APU curves for SL2P-CCRS/L8 and SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR, as well as the partition (histogram) of samples used to fit APU curves. The increased samples density for the different variable’s levels explains the narrow confidence interval of APU models. 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 for LAI, ~100 for fCOVER and ~180 samples for fAPAR, regardless the sensor).

APU curves associated to SL2P-CCRS/L8 estimates compares well with the corresponding curves associated to SL2P-CCRS/L8 estimates, regardless the vegetation variable. In fact, 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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Figure 4: APU curves and the corresponding 95% confidence intervals (dashed contours) for SL2P-CCRS/L8 and SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR. Dashed grey lines bound target user requirements. (add APU for intercomparison, S2 is the ref)

* 1. Cross-comparison

Figure 7 shows density contour plots of SL2P-CCRS/S2 LAI, fCOVER and fAPAR estimates versus the corresponding estimates from SL2P-CCRS/L8. Estimates for unforested classes are merged for three raisons: the small sample size for some classes, the similarity of contours behaviour (not shown), and the simplicity of figures. Figure 8 shows class specific thematic statistics.

About 32000 samples of SL2P-CCRS/L8 estimates of LAI, fCOVER and fAPAR (each) are compared to the corresponding SL2P-CCRS/S2 estimates acquired within +/-1 day (Table 1, Appendix D). Biggest samples sizes are for evergreen forest, grassland herbaceous, deciduous forest, and shrub scrub with more than 5000 samples. While, the smallest samples sizes are for sedge herbaceous, pasture hay, emergent herbaceous wetlands and cultivate crops (between 280 and 1000 samples).

SL2P-CCRS/L8 estimates of LAI, fCOVER and fAPAR generally compares well to the corresponding SL2P-CCRS/S2 estimates: R2>0.85 for the different variables, A~0.04 (~0.01) for LAI (fCOVER and fAPAR) and U ~0.54 (~0.09) for fCOVER and fAPAR (Table 1, Appendix D).

Figure 7 indicates that, SL2P-CCRS/L8 underestimate LAI in comparison to SL2P-CCRS/S2 estimates for deciduous and mixed forests (more pronounced underestimation ~-1.5 for high LAI values ~5) in contrast to the other classes, with LAI estimates not exceeding 4 units in general, which fit well with 1:1. For too low LAI values (<1) SL2P-CCRS/L8 generally overestimate LAI from SL2P-CCRS/L8 for the different classes. For fCOVER and fAPAR, density contours plots fit well with 1:1 line with a slight underestimation (~-0.05) for high values. Similarly, for short vegetation (fCOVER or fAPAR<0.2) SL2P-CCRS/L8 fCOVER and fAPAR generally overestimate the corresponding estimates from SL2P-CCRS/S2 for different classes.

Except for emergent herbaceous wetlands and sedge herbaceous, which have the smallest samples sizes and the narrowest variation ranges (Figure 8), R2 ranges between 0.63 (pasture hay) and 0.90 (cultivated crops) for LAI, between 0.77 (mixed forest and grassland herbaceous) and 0.93 (cultivated crops) for fCOVER, and between 0.76 (mixed forest) and 0.94 (cultivated crops) for fAPAR. The accuracy ranges between -0.33 (deciduous forest) and 0.16 (shrub scrub) for LAI, between -0.03 (deciduous forest and mixed forest) and 0.06 (sedge herbaceous) for fCOVER, and between -0.04 (evergreen forest) and 0.06 (sedge herbaceous) for fAPAR. The uncertainty ranges between 0.30 (shrub scrub) and 0.83 (deciduous forest) for LAI, between 0.06 (shrub scrub) and 0.10 (deciduous forest, mixed forest, grassland herbaceous and pasture hay), and between 0.06 (shrub scrub) and 0.10 (deciduous forest, mixed forest and pasture hay) for fAPAR.

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Figure 7: Density contour plots of SL2P-CCRS/S2 estimates of (a) LAI, (b) fCOVER and (c) fAPAR (x-axis) versus the corresponding SL2P-CCRS/L8 estimates (y-axis): continuous and dashed lines are the 0.5 and 0.1 quantiles respectively.

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Figure 8: Class specific thematic statistics between SL2P-CCRS/S2 LAI, fCOVER and fAPAR estimates (reference) compared to the corresponding estimates from SL2P-CCRS/L8 together with the samples size (histogram) and the variation range of estimates from SL2P-CCRS/S2 (orange bars).

* 1. Temporal stability of SL2P-CCRS 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 6.a: 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 6.b: 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. Discussions
2. Conclusions
3. References

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Appendix A

Table 1: Number of ESUs, sampling period, number of acquired samples, and NLCD classes for CCRS and NEON sites.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **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** |  |

Appendix B

A graph of data showing the number of data

Description automatically generated with medium confidence

Figure 1: Example of outliers detected on RM time series acquired on site GUAN\_054

Table 1: Number and percentage (compared to the sample size) of outliers detected for each variable and NLCD class.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | fCOVER | | | fAPAR | | |
| NLCD | #N | #Outliers | % | #N | #Outliers | % | #N | #Outliers | % |
| EF | 3427 | 3 | 0.09 | 3427 | 30 | 0.88 | 3427 | 16 | 0.47 |
| GH | 2101 | 1 | 0.05 | 2101 | 4 | 0.19 | 2101 | 3 | 0.14 |
| SS | 1704 | 0 | 0 | 1704 | 1 | 0.06 | 1704 | 1 | 0.06 |
| MF | 639 | 1 | 0.16 | 639 | 1 | 0.16 | 639 | 1 | 0.16 |
| SH | 126 | 0 | 0 | 126 | 0 | 0 | 126 | 0 | 0 |
| EHW | 79 | 0 | 0 | 79 | 0 | 0 | 79 | 0 | 0 |
| DF | 3923 | 19 | 0.48 | 3923 | 28 | 0.71 | 3923 | 31 | 0.79 |
| PH | 934 | 16 | 1.71 | 934 | 55 | 5.89 | 934 | 48 | 5.14 |
| CC | 702 | 2 | 0.28 | 702 | 16 | 2.28 | 702 | 16 | 2.28 |
| WW | 326 | 2 | 0.61 | 326 | 2 | 0.61 | 326 | 2 | 0.61 |
| ~~DS~~ | ~~180~~ | ~~0~~ | ~~0~~ | ~~180~~ | ~~0~~ | ~~0~~ | ~~180~~ | ~~0~~ | ~~0~~ |
| **Total** | **14141** | **44** | **0.31** | **14141** | **137** | **0.97** | **14141** | **118** | **0.83** |

Appendix C

A graph of a function

Description automatically generated

A diagram of a function

Description automatically generated

A diagram of a function

Description automatically generated

Figure 1: Scatter plots of LAI, fCOVER and fAPAR estimates from SL2P-CCRS/L8 versus matching RMs for (a) BARR, (b) TOOL and (c) DEJU sites, together with population validation metrics. Dashed lines bound target user requirement around solid 1:1 line.

Appendix D

A diagram of different colored shapes

Description automatically generated with medium confidence

Figure 2.2: Scatter plots of SL2P-CCRS/S2 estimates of LAI, fCOVER and fAPAR versus matching RMs together with population validation metrics. Dashed lines bound target user requirement around solid 1:1 line.

Table 1: R2, A, P and U statistics for SL2P-CCRS/L8 LAI, fCOVER and fAPAR estimates compared to RMs, as well as the samples size (N) and the variation range (min max) of RMs.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | | | | fCOVER | | | | | | fAPAR | | | | | |
| NLCD | EHW | 35 | 0.57 | 0.13 | 0.32 | 0.58 | 2.02 | 35 | 0.61 | 0.05 | 0.09 | 0.13 | 0.58 | 35 | 0.78 | 0.03 | 0.07 | 0.16 |
| EHW | SH | 69 | 0.41 | 0.01 | 0.22 | 0.71 | 1.88 | 69 | 0.54 | 0.02 | 0.07 | 0.24 | 0.61 | 69 | 0.48 | 0.02 | 0.07 | 0.22 |
| SH | CC | 246 | 0.80 | 0.32 | 0.52 | 0.08 | 4.13 | 246 | 0.79 | 0.12 | 0.16 | 0.00 | 0.84 | 246 | 0.83 | 0.07 | 0.12 | 0.03 |
| CC | PH | 403 | 0.68 | 0.39 | 0.59 | 0.57 | 3.82 | 403 | 0.68 | 0.11 | 0.17 | 0.04 | 0.84 | 403 | 0.68 | 0.06 | 0.13 | 0.03 |
| PH | SS | 614 | 0.92 | 0.27 | 0.68 | 0.20 | 5.96 | 614 | 0.89 | 0.06 | 0.10 | 0.00 | 0.96 | 614 | 0.89 | 0.05 | 0.10 | 0.00 |
| SS | GH | 1139 | 0.70 | 0.39 | 0.59 | 0.10 | 5.71 | 1139 | 0.75 | 0.11 | 0.15 | 0.00 | 0.94 | 1139 | 0.77 | 0.08 | 0.13 | 0.01 |
| GH | WW | 140 | 0.68 | -1.54 | 1.92 | 0.57 | 5.43 | 140 | 0.56 | -0.10 | 0.17 | 0.19 | 0.88 | 140 | 0.45 | -0.18 | 0.23 | 0.18 |
| WW | MF | 319 | 0.74 | -1.31 | 1.52 | 0.51 | 4.70 | 319 | 0.84 | -0.05 | 0.09 | 0.18 | 0.89 | 319 | 0.73 | -0.12 | 0.15 | 0.17 |
| MF | DF | 1830 | 0.73 | -1.26 | 1.70 | 0.03 | 5.67 | 1830 | 0.75 | -0.04 | 0.13 | 0.03 | 0.95 | 1830 | 0.72 | -0.09 | 0.15 | 0.03 |
| DF | EF | 1846 | 0.53 | -0.76 | 1.43 | 0.03 | 4.48 | 1846 | 0.55 | -0.05 | 0.17 | 0.01 | 0.87 | 1846 | 0.50 | -0.13 | 0.21 | 0.02 |
| EF | All | 6641 | 0.77 | -0.53 | 1.30 | 0.03 | 5.96 | 6641 | 0.78 | 0.01 | 0.14 | 0.00 | 0.96 | 6641 | 0.74 | -0.05 | 0.16 | 0.00 |
| All | EHW | 35 | 0.57 | 0.13 | 0.32 | 0.58 | 2.02 | 35 | 0.61 | 0.05 | 0.09 | 0.13 | 0.58 | 35 | 0.78 | 0.03 | 0.07 | 0.16 |

Table 2: R2, A, P and U statistics for SL2P-CCRS/S2 LAI, fCOVER and fAPAR estimates compared to RMs, as well as the samples size (N) and the variation range (min max) of RMs.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | | | | fCOVER | | | | | | fAPAR | | | | | |
| NLCD | N | R2 | A | U | min | max | N | R2 | A | U | min | max | N | R2 | A | U | min | max |
| EHW | 40 | 0.47 | 0.27 | 0.37 | 0.16 | 1.88 | 40 | 0.54 | 0.02 | 0.06 | 0.03 | 0.41 | 40 | 0.51 | 0.02 | 0.07 | 0.04 | 0.41 |
| SH | 79 | 0.23 | 0.12 | 0.33 | 0.74 | 2.37 | 79 | 0.56 | 0.01 | 0.07 | 0.21 | 0.64 | 79 | 0.52 | 0.01 | 0.07 | 0.21 | 0.62 |
| CC | 163 | 0.78 | 0.38 | 0.58 | 0.01 | 4.03 | 163 | 0.78 | 0.10 | 0.15 | 0.00 | 0.90 | 163 | 0.82 | 0.07 | 0.12 | 0.01 | 0.88 |
| PH | 319 | 0.62 | 0.46 | 0.66 | 0.15 | 4.86 | 319 | 0.63 | 0.11 | 0.17 | 0.06 | 0.88 | 319 | 0.68 | 0.06 | 0.13 | 0.08 | 0.86 |
| SS | 420 | 0.86 | 0.17 | 0.66 | 0.00 | 6.08 | 420 | 0.87 | 0.07 | 0.11 | 0.00 | 0.92 | 420 | 0.87 | 0.05 | 0.10 | 0.00 | 0.90 |
| GH | 747 | 0.74 | 0.28 | 0.61 | 0.00 | 4.95 | 747 | 0.80 | 0.10 | 0.14 | 0.00 | 0.90 | 747 | 0.82 | 0.05 | 0.12 | 0.00 | 0.85 |
| WW | 84 | 0.54 | -1.87 | 2.17 | 0.63 | 5.31 | 84 | 0.48 | -0.12 | 0.18 | 0.17 | 0.89 | 84 | 0.41 | -0.19 | 0.23 | 0.18 | 0.88 |
| MF | 195 | 0.83 | -1.01 | 1.22 | 0.29 | 5.22 | 195 | 0.85 | -0.01 | 0.09 | 0.03 | 0.92 | 195 | 0.78 | -0.10 | 0.14 | 0.01 | 0.89 |
| DF | 1330 | 0.72 | -0.87 | 1.37 | 0.08 | 6.87 | 1330 | 0.73 | -0.02 | 0.13 | 0.01 | 0.99 | 1330 | 0.72 | -0.08 | 0.15 | 0.04 | 0.95 |
| EF | 1558 | 0.49 | -0.88 | 1.53 | 0.16 | 5.00 | 1558 | 0.50 | -0.03 | 0.17 | 0.05 | 0.87 | 1558 | 0.47 | -0.12 | 0.21 | 0.06 | 0.84 |
| All | 4935 | 0.73 | -0.48 | 1.23 | 0.00 | 6.87 | 4935 | 0.75 | 0.01 | 0.15 | 0.00 | 0.99 | 4935 | 0.72 | -0.05 | 0.16 | 0.00 | 0.95 |

Appendix E

Table 1: Class specific statistics between SL2P-CCRS/S2 versus SL2P-CCRS/L8 as well as the samples size and the variation range of estimates from SL2P-CCRS/S2 (reference)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LAI | | | | | | fCOVER | | | | | | fAPAR | | | | | |
| **NLCD** | **N** | **R2** | **A** | **U** | **min** | **max** | **N** | **R2** | **A** | **U** | **min** | **max** | **N** | **R2** | **A** | **U** | **min** | **max** |
| CC | 854 | 0.90 | 0.10 | 0.40 | 0.11 | 5.12 | 797 | 0.93 | 0.03 | 0.08 | 0.00 | 0.92 | 990 | 0.94 | 0.04 | 0.07 | 0.02 | 0.90 |
| DF | 6496 | 0.83 | -0.33 | 0.83 | 0.06 | 6.06 | 6501 | 0.89 | -0.03 | 0.10 | 0.01 | 0.97 | 6499 | 0.88 | -0.03 | 0.10 | 0.03 | 0.94 |
| EHW | 559 | 0.34 | 0.05 | 0.56 | 0.06 | 2.76 | 563 | 0.49 | 0.02 | 0.12 | 0.04 | 0.66 | 566 | 0.49 | 0.02 | 0.12 | 0.05 | 0.65 |
| EF | 7850 | 0.80 | -0.07 | 0.40 | 0.01 | 4.70 | 7853 | 0.84 | -0.03 | 0.08 | 0.00 | 0.85 | 7851 | 0.83 | -0.04 | 0.08 | 0.00 | 0.83 |
| GH | 6533 | 0.73 | 0.14 | 0.39 | 0.01 | 5.92 | 6601 | 0.77 | 0.02 | 0.10 | 0.00 | 0.95 | 7285 | 0.80 | 0.03 | 0.09 | 0.00 | 0.92 |
| MF | 1358 | 0.72 | -0.09 | 0.66 | 0.53 | 4.83 | 1357 | 0.77 | -0.03 | 0.10 | 0.06 | 0.90 | 1357 | 0.76 | -0.03 | 0.10 | 0.02 | 0.88 |
| PH | 530 | 0.63 | -0.02 | 0.65 | 0.34 | 5.54 | 533 | 0.78 | 0.01 | 0.10 | 0.07 | 0.93 | 535 | 0.78 | 0.01 | 0.10 | 0.07 | 0.91 |
| SH | 287 | 0.26 | 0.07 | 0.33 | 0.65 | 2.15 | 287 | 0.51 | 0.06 | 0.10 | 0.17 | 0.62 | 287 | 0.47 | 0.06 | 0.10 | 0.18 | 0.60 |
| SS | 5613 | 0.83 | 0.16 | 0.30 | 0.14 | 5.56 | 5055 | 0.85 | -0.01 | 0.06 | 0.00 | 0.94 | 5276 | 0.83 | 0.00 | 0.06 | 0.00 | 0.91 |
| WW | 2072 | 0.77 | -0.23 | 0.69 | 0.37 | 4.93 | 2069 | 0.83 | -0.02 | 0.09 | 0.04 | 0.90 | 2069 | 0.84 | -0.03 | 0.09 | 0.08 | 0.87 |
| **All** | **32152** | **0.85** | **-0.04** | **0.54** | **0.01** | **6.06** | **31616** | **0.88** | **-0.01** | **0.09** | **0.00** | **0.97** | **32715** | **0.88** | **-0.01** | **0.09** | **0.00** | **0.94** |