**On the consistency and stability of vegetation biophysical variables retrievals from Landsat-8/9 and Sentinel-2**

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**Abstract**

Systematic medium (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. The Canada Centre for Remote Sensing version of the Simplified Level 2 Prototype Processor (SL2P-CCRS) is available as a baseline solution for the global mapping of those variable using freely available medium resolution multilateral satellite data from Sentinel-2 (S2) and Landsat-8/9 (LS) data.

Fiducial reference measurements from the Canada Centre for Remote Sensing sites and National Ecological Observatory Network, with 10 different vegetation classes, are used to evaluate the consistency of SL2P-CCRS estimates of LAI, fCOVER and fAPAR from LS data with the corresponding estimates from S2 and evaluate their temporal stabilities.

Results indicates that, LAI estimates from LS data (6569 samples) underestimates RMs (A~0.43, U~1.13) in contrast to fCOVER and fAPAR estimates which are ~unbiased (U~13). Comparable statistic results are obtained for estimates from S2 data, except for LAI which fits better with RMs (A~-0.33, U~0.98) compared to LAI estimates from LS, mainly for forested sites. This result is confirmed when comparing ~47000 samples of SL2P-CCRS estimates from LS to the corresponding estimates from S2 acquired within +/1 day. In fact, linear relationship is obtained between estimates from LS and the corresponding estimates from S2 (R20.98) for the different variables. Estimates from LS compares well with the corresponding estimates from S2 for fCOVER and fAPAR (A~-0.01, U~0.07) and LAI over unforested sites (A from -0.01 to 0.15, U from 0.17 to 0.38 ), while LAI estimates from LS for forested site are found underestimated (A from ~-0.10 to ~0.34, U from 0.38 to 0.80) when compared to the corresponding estimates from S2. On other side, SL2P-CCRS estimates of LAI, fCOVER and fAPAR from LS showed high level of stability (S~0) over ~1-decade, while the stability of SL2P-CCRS estimates from S2 date is found not significant due to the short period of estimates.

Keywords : LAI, fCOVER, fAPAR, SL2P-CCRS, Landsat-8/9 (LS), Sentinel-2 (S2), validation, consistency, stability

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 LS 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 vegetation variables estimate from LS products will result in significantly greater uncertainty compared to estimates from S2 due to increased bias due to modelling and local validation studies (xx). We also hypothesize that SL2P-CCRS/LS and SL2P-CCRS/S2 estimates 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 LS products and indeed a Stage 3 validation using a free and open globally applicable algorithm, (2) it propose a new approach to quantifying stability relying on a new extended NEON RMs dataset, (3) and it present a basis for the first medium resolution ECV CDR when the LS data reaches temporal extent for relevance in climate studies.

Impact

* A, P, U and bias correction results for LS for areas represented by NEON sites.
* Uncertainty of annual trends and anomalies of ECVs derived from LS 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 site 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 classes: EF, DF and MF.

Table 1: NLCD classes for used RMs (forested classes are in bold)

|  |  |  |
| --- | --- | --- |
| **NLCD class** | **Abbreviate** | **#ESUs** |
| **Evergreen forest** | **EF** | **311** |
| **Deciduous forest** | **DF** | **256** |
| **Mixed forest** | **MF** | **58** |
| **Woody wetlands** | **WW** | **88** |
| Cultivated crops | CC | 50 |
| Emergent herbaceous wetlands | EHW | 19 |
| Grassland herbaceous | GH | 165 |
| Pasture hay | PH | 32 |
| Sedge herbaceous | SH | 20 |
| Shrub scrub | SS | 139 |
| Dwarf scrub | DS | 22 |

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Figure 1. NEON and CCRS sites across North America, 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 (DHPs) 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 in Appendix A.
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 location (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.
   1. Satellite data

Surface reflectance (SR) 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.

LS 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 SR 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: LS-OLI bands (SL2P-CCRS input bands are in bold)

|  |  |  |  |
| --- | --- | --- | --- |
| Band | Resolution (m) | 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 (m) | Central Wavelength (nm) | Description |
| B1 | 60 | 443 | Coastal / Aerosol |
| B2 | 10 | 490 | Blue |
| **B3** | **10** | **560** | **Green** |
| **B4** | **10** | **665** | **Red** |
| **B5** | **20** | **705** | **Vegetation red edge** |
| **B6** | **20** | **740** | **Vegetation red edge** |
| **B7** | **20** | **783** | **Vegetation red edge** |
| B8 | 10 | 842 | **Near-Infrared** |
| **B8a** | **20** | **865** | **Near-Infrared** |
| B9 | 60 | 940 | Water vapour |
| B10 | 60 | 1375 | Cirrus |
| **B11** | **20** | **1610** | **Short Wave Infrared** |
| **B12** | **20** | **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 estimates 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 (LS) 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 DHPs acquisition date are extracted to ensure that at least three satellite acquisitions for each sample date given the < 8-days (5-days) revisit of LS (S2) imagers. 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 (Table 1). 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 in 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 estimates from LS and S2 are 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 estimates from LS and S2 as detailed in Fernandes et al. (2024).

* 1. Inter-comparison

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

* 1. Temporal stability.

The stability (S) of LAI, fCOVER and fAPAR estimates obtained using SL2P-CCRS from LS and S2 was quantified 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.

S was estimates as the slope of ordinary least squares regression of estimated annual bias, which is computed 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 annual bias samples were retained to minimize the impact of sample size on the precision of the bias estimate.

The mean and the standard deviation of annual bias values, as well as the 95% Confidence Interval (CI) of S were used to quantify the precision of the stability estimate.

1. Results
   1. Cross-validation

Figure 2 presents scatter plots of SL2P-CCRS estimates of LAI, fCOVER and fAPAR from LS data against RMs together with population validation metrics. A total of 6569 matchups were obtained, with RMs ranging from 0.02 to 5.88 for LAI, from 0 to 0.96 for fCOVER, and from 0 to 0.93 for fAPAR (Table 1 in Appendix D). Figure 1 in Appendix D presents scatter plots obtained for SL2P-CCRS estimates S2 data (already validated in Fernandez et al., 2024).

Figure 2 indicates that despite the linear relationships between estimates and RMs (R2 ~0.80), SL2P-CCRS/LS underestimates LAI (A=-0.43, U=1.13). This explains the low UAR (~0.10) obtained for LAI estimates. Conversely, fCOVER and fAPAR estimates are ~unbiased, with comparable uncertainty (~0.13), R2 (~80), and UAR40% values.

In general, validation statistics obtained for SL2P-CCRS estimates from LS are comparable to validation statistics obtained for the corresponding estimates from S2 data, except for LAI; slightly better results are obtained using S2 (A=-0.33, U= 0.98).

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

Figure 3 presents class specific A, U and UAR statistics, as well as the class specific sample size. Similarly, it indicates that comparable statistics are generally obtained for SL2P-CCRS estimates from LS and the corresponding estimates from S2 regardless the vegetation class. SL2P-CCRS estimates are underestimated irrespective to the sensor (LS or S2) and the vegetation variable for woody wetlands, evergreen forest, deciduous forest, and mixed forest: A ranges from -1.73 to -0.38 for LAI, from -0.11 to 0 for fCOVER, and from -0.17 to -0.06 for fAPAR. The underestimation is always higher for woody wetlands and lower for evergreen forest. While estimates are slightly overestimated for the other classes: from 0.01 to 0.45 for LAI, from 0.01 to 0.11 for fCOVER, and from 0.01 to 0.08 for fAPAR.

The uncertainty of LAI and fAPAR estimates is generally higher for forested sites (from 0.81 to 1.99 for LAI, from 0.13 to 0.22 for fAPAR) compared to unforested sites (from 0.22 to 1.67 for LAI, from 0.0.06 to 0.13 for fAPAR), but no clear trend observed for fCOVER estimates (ranging from 0.06 to 0.17)

UAR

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Figure 3: Class specific A, U and UAR statistics for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from LS and S2 data against RMs together with used samples size (histograms).

Figure 4 shows APU curves for SL2P-CCRS estimates of LAI, fCOVER and fAPAR from LS compared to APU curves for the corresponding estimates from S2, together with used samples partition (histograms). 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 ~150 for fAPAR, regardless the sensor).

APU curves for estimates from SL2P-CCRS/S2 and the corresponding curves from for estimates from SL2P-CCRS/S2 have very similar trends, but with small differences in absolute values. In fact, the accuracy of LAI estimates from LS ~linearly decrease from ~0.8 for LAI<1 to ~-3 for LAI~7, in contrast to the uncertainty which increase from ~0.5 for LAI<1 to ~3 for LAI~7 (satisfying GCOS requirements only for LAI<3). While the precision is ~stable between 0 and 0.6 for the entire values range. For LAI<3, APU values from LS are comparable to values obtained for estimates from S2. However, for LAI> the accuracy (uncertainty) of estimates from LS is up to ~1 unit lower (higher) than the accuracy (uncertainty) of estimates from S2, introducing a slightly lower precision values for estimates from LS.

For fCOVER, the accuracy and the uncertainty of LS estimates simultaneously increase from ~0.1 to ~0.14 for the range 0 - 0.2, then decrease to ~-0.08 (accuracy) and ~0.07 (uncertainty) for the range 0.2-0.8, and finally increase to ~0 (accuracy) and 0.2 (uncertainty) for the range 0.8-1. While the precision remains ~stable between ~0.05 and 0.10 for the entire range. Target uncertainty requirements are only satisfied for fCOVER from 0.5 to 0.9. fCOVER estimates from LS showed slightly higher uncertainty (up to ~0.03) and absolute accuracy (up to ~0.04) compared to estimates from S2 with comparable precision values.

The accuracy of fAPAR estimates from LS decreases from ~ 0.12 for fAPAR~ 0 to ~-0.12 for fAPAR~1, while the uncertainty decreases from ~0.11 to ~0.09 for the range 0 - 0.5, then it increases back to ~0.2 for the range 0.5 - 1. The precision remains ~stable between 0.07 and 0.10 for the entire range. Compared to APU curves for estimates from S2, higher absolute accuracy values (up to ~0.04) and uncertainty (up to 0.03) are observed for estimates from LS for fAPAR<1.5 and fAPAR >0.7.

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Figure 4: APU curves and the corresponding 95% confidence intervals (dashed contours) for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from LS compared to APU curves for the corresponding estimates from S2. Dashed grey lines bound target user requirements.

* 1. Inter-comparison

Figure 5 shows density contour plots comparing SL2P-CCRS estimates from LS to the corresponding estimates S2 acquired with +/- 1-day (reference). More than 47000 matchups for each variable are used (Table 1 in Appendix E). Evergreen forest, deciduous forest, shrub scrub, and grassland herbaceous have the largest sample sizes (N>8000), while the smallest sample sizes (N<1000) are for sedge herbaceous, emergent herbaceous wetlands and pasture hay.

Samples for unforested classes are merged with for three raisons: the small sample sizes for some classes, the similarity of contours behaviour (not shown), and for the simplicity of figures. Figure 6 and Table 1 in Appendix E shows class specific thematic statistics.

Linear relationships are noted between SL2P-CCRS estimates from LS and the corresponding estimates from S2 regardless to the vegetation variable (, Figure 5), even for class specific cases (), except for emergent herbaceous wetlands and sedge herbaceous ( up to 0.76) with the smallest sample sizes and the narrowest variation ranges.

Retrievals from LS underestimates retrievals from LS mainly for LAI (A =-0.07, U=0.5), while for fCOVER and fAPAR density contours plots fit better with 1:1 line (A~-0.01, U ~0.07, Table 1 in Appendix E).

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Figure 5: Density contour plots of SL2P-CCRS estimates of (a) LAI, (b) fCOVER and (c) fAPAR from LS data compared to the corresponding estimates from S2 data (reference): continuous (dashed) lines present 0.5 (0.1) quantiles.

The underestimation SL2P-CCRS LAI estimates from LS when compared to the corresponding estimates from S2 is restricted to evergreen forest (A~-0.10, extreme lower case), mixed forest (A~-0.13), woody wetland (A~-0.22), and mainly deciduous forest (A~-0.34, extreme upper case). Evergreen forest, mixed forest, woody wetland, and deciduous forest have also the highest uncertainty values: 0.38, 0.56, 0.61 and 0.80, respectively. For the other classes, the accuracy ranges between -0.01 and 0.15, and the uncertainty between 0.17 and 0.38.

For fCOVER and fAPAR, even though the underestimation is negligible in general (~-0.01 overall), woody wetland, evergreen forest, mixed forest, and deciduous forest showed, again, the largest underestimation (from -0.02 to -0.04) in comparison to the other classes (from -0.01 to 0.04).

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Figure 6: Class specific R2, A and U statistics between SL2P-CCRS estimates of LAI, fCOVER and fAPAR from LS and the corresponding estimates from S2 (reference), together with the samples size (histogram) and the variation range of estimates from S2 (bars).

* 1. Temporal stability of SL2P-CCRS vegetation variable estimates

Figure 7 shows the variation of annual bias of LAI estimates for all sites merged obtained using SL2P-CCRS from LS and S2 data between 2014 (2019 for S2) and 2022, as well as the size of used samples. Annual bias values are computed with at least ~200 samples/year for LS and at least 700 samples/year for S2.

Results indicates that LAI estimates from LS are quite stable during 9-years of estimates (S ~ 0 with CI=0.04). Annual bias values range between ~-0.71 and -0.34 units with an average of -0.45 and a standard deviation of 0.12.

Results for LAI estimates from S2 are not conclusive since they cover a shorter period of time (4-years). Nerveless, annual bias values for LAI estimates from S2 data fit well with corresponding values obtained for estimates from LS data during the overlapping period (from 2019 to 2022). Similar results are obtained for fCOVER and fAPAR (S=0 with CI=0) estimates (not shown to avoid complexity).

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Figure 7: Annual bias profile with S indicated for SL2P-CCRS estimates of LAI obtained from LS and S2 data for all sites merged.

The stability of SL2P-CCRS estimates from LS and S2 data is further investigated at site basis. Only S values and the associated confidence intervals are reported to avoid complexity. Figure 8.1 shows scatter plots of S versus the annual bias mean value for LAI, fCOVER and fAPAR estimates from LS data over 46 NEON sites with different NLCD classes. It is noted that (i) S values range from ~-0.15 to 0.08 (mean ~ -0.01, standard-deviation ~ 0.06) for LAI, and from -0.02 to 0.02 (mean ~ 0, standard-deviation ~ 0.01) for fCOVER and fAPAR, and (ii) SL2P-CCRS estimates for forested sites (big circles at the bottom, generally underestimated) are generally less stable than estimates for unforested sites (small circles at the top, generally overestimated), mainly for LAI.

For estimates from S2 data, despite the shorter covered period (unconclusive results), comparable to S values are generally observed for estimates from S2 data (Figure 8.2), but with larger CI. In fact, S values range between -0.17 and 0.25 (mean ~ 0.02, standard deviation ~ 0.09) for LAI, and from -0.03 to 0.03 (mean ~0, standard deviation ~0.01) for fCOVER and fAPAR.

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Figure 8.1: Scatter plots of S versus annual bias mean for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from LS data: x error bars (S confidence interval), y error bars (annual bias standard deviation), circles size (RM mean), and color (NLCD class).

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Figure 8.2: Scatter plots of S versus annual bias mean for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from S2 data: x error bars (S confidence interval), y error bars (annual bias standard deviation), circles size (RM mean), and color (NLCD class).

1. Discussions

Dataset

* Huge validation dataset with multiple land covers
* Outliers
* Unbalanced sample size
* Difference in S2 and L8 footprints

Important results

* Compared to RMs, comparable results are generally obtained using SL2P-CCRS from LS and S2 for fCOVER and fAPAR, but better results using S2 for LAI.
* SL2P-CCRS underestimate LAI for both sensors (-0.42 using LS and -0.32 using S2)
* ~Unbaised fCOVER and fAPAR for both sensors
* Low UAR (~0.10 for LAI, 0.40 for fCOVER and 0.35 for fAPAR)
* SL2P-CCRS underestimate vegetation variables for forested sites (WW, DF, EF and MF).
* SL2P-CCRS slightly overestimate vegetation variables for unforested sites.
* The uncertainty (and the absolute value of the accuracy) generally increases with the absolute value of vegetation variable.
* The precision of estimates from LS and S2 is ~stable.

LS/S2 intercomparison indicates that:

* Linear relationship between SL2P-CCRS estimates from LS vs. estimates from S2. But SL2P-CCRS estimates from LS are generally underestimated when compared to estimates from S2, mainly for LAI.
* The underestimation is more pronounced for Forested sites (mainly for DF).

Stability:

* SL2P-CCRS estimates from LS data showed a stability over time (~1-decade of estimates),
* No conclusion could be made for estimates from S2 due to the short period of available data (4-years), but it seems comparing well with LS trend.

Future work

* Comparing estimates from HLSS30 to estimates from HLSL30: same atmospheric correction algo but different radiometry.
* Bias correction of other approach to improve estimates from forested sites.
* Stability of estimates from S2 (longer study period).

1. Conclusions
2. 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** |  |

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

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

Appendix B

A graph of data showing the number of data

Description automatically generated with medium confidence

Figure 1: Example of outliers detected on RMs time series acquired on NEON site GUAN (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 SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from S2 data 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 a graph

Description automatically generated with medium confidence

Figure 1: Scatter plots of SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from S2 data 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 estimates of LAI, fCOVER and fAPAR from LS data versus matching 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 | 35 | 0.57 | 0.12 | 0.31 | 0.58 | 2.07 | 35 | 0.65 | 0.04 | 0.09 | 0.12 | 0.61 | 35 | 0.83 | 0.03 | 0.07 | 0.14 | 0.59 |
| SH | 69 | 0.40 | 0.01 | 0.22 | 0.71 | 1.88 | 69 | 0.56 | 0.02 | 0.07 | 0.24 | 0.61 | 69 | 0.51 | 0.02 | 0.07 | 0.22 | 0.59 |
| CC | 234 | 0.79 | 0.30 | 0.50 | 0.08 | 3.95 | 234 | 0.82 | 0.11 | 0.15 | 0.00 | 0.84 | 234 | 0.86 | 0.07 | 0.11 | 0.03 | 0.83 |
| PH | 383 | 0.68 | 0.39 | 0.59 | 0.57 | 3.81 | 383 | 0.69 | 0.11 | 0.17 | 0.04 | 0.85 | 383 | 0.68 | 0.06 | 0.13 | 0.03 | 0.83 |
| SS | 614 | 0.92 | 0.26 | 0.67 | 0.19 | 5.88 | 614 | 0.90 | 0.06 | 0.10 | 0.00 | 0.96 | 614 | 0.89 | 0.05 | 0.10 | 0.00 | 0.93 |
| GH | 1136 | 0.72 | 0.38 | 0.57 | 0.10 | 5.64 | 1136 | 0.76 | 0.11 | 0.15 | 0.00 | 0.93 | 1136 | 0.78 | 0.08 | 0.13 | 0.01 | 0.91 |
| WW | 138 | 0.72 | -1.50 | 1.87 | 0.58 | 5.40 | 138 | 0.61 | -0.09 | 0.16 | 0.19 | 0.89 | 138 | 0.46 | -0.17 | 0.22 | 0.18 | 0.86 |
| MF | 319 | 0.75 | -1.30 | 1.51 | 0.52 | 4.72 | 319 | 0.85 | -0.05 | 0.09 | 0.16 | 0.89 | 319 | 0.73 | -0.11 | 0.15 | 0.18 | 0.86 |
| DF | 1816 | 0.74 | -1.27 | 1.68 | 0.03 | 5.53 | 1816 | 0.76 | -0.04 | 0.12 | 0.03 | 0.94 | 1816 | 0.73 | -0.09 | 0.15 | 0.03 | 0.91 |
| EF | 1825 | 0.67 | -0.38 | 0.82 | 0.02 | 4.28 | 1825 | 0.71 | -0.01 | 0.12 | 0.01 | 0.87 | 1825 | 0.67 | -0.08 | 0.14 | 0.02 | 0.85 |
| **All** | **6569** | **0.82** | **-0.43** | **1.13** | **0.02** | **5.88** | **6569** | **0.83** | **0.02** | **0.13** | **0.00** | **0.96** | **6569** | **0.80** | **-0.03** | **0.14** | **0.00** | **0.93** |

Table 2: R2, A, P and U statistics for SL2P-CCRS estimates of LAI, fCOVER and fAPAR from S2 data versus matching 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 | 0.49 | 0.26 | 0.35 | 0.12 | 1.70 | 40 | 0.54 | 0.02 | 0.06 | 0.03 | 0.41 | 40 | 0.51 | 0.02 | 0.06 | 0.04 | 0.41 |
| SH | 79 | 0.24 | 0.11 | 0.32 | 0.59 | 2.37 | 79 | 0.58 | 0.01 | 0.07 | 0.21 | 0.64 | 79 | 0.54 | 0.01 | 0.07 | 0.21 | 0.62 |
| CC | 163 | 0.77 | 0.36 | 0.57 | 0.01 | 4.03 | 163 | 0.79 | 0.10 | 0.15 | 0.00 | 0.90 | 163 | 0.82 | 0.07 | 0.12 | 0.01 | 0.88 |
| PH | 319 | 0.63 | 0.45 | 0.66 | 0.15 | 4.85 | 319 | 0.64 | 0.11 | 0.17 | 0.06 | 0.88 | 319 | 0.69 | 0.06 | 0.13 | 0.07 | 0.86 |
| SS | 420 | 0.86 | 0.17 | 0.66 | 0.00 | 5.89 | 420 | 0.88 | 0.07 | 0.11 | 0.00 | 0.92 | 420 | 0.88 | 0.05 | 0.10 | 0.00 | 0.90 |
| GH | 747 | 0.75 | 0.27 | 0.60 | 0.00 | 4.95 | 747 | 0.81 | 0.10 | 0.14 | 0.00 | 0.90 | 747 | 0.83 | 0.05 | 0.11 | 0.00 | 0.85 |
| WW | 83 | 0.63 | -1.73 | 1.99 | 0.63 | 5.38 | 83 | 0.52 | -0.11 | 0.17 | 0.20 | 0.91 | 83 | 0.46 | -0.17 | 0.21 | 0.18 | 0.89 |
| MF | 195 | 0.84 | -1.01 | 1.21 | 0.29 | 5.22 | 195 | 0.86 | -0.01 | 0.09 | 0.03 | 0.92 | 195 | 0.80 | -0.09 | 0.13 | 0.01 | 0.89 |
| DF | 1330 | 0.73 | -0.87 | 1.36 | 0.10 | 6.87 | 1330 | 0.74 | -0.02 | 0.13 | 0.01 | 0.99 | 1330 | 0.73 | -0.08 | 0.15 | 0.04 | 0.95 |
| EF | 1556 | 0.66 | -0.39 | 0.81 | 0.16 | 5.00 | 1556 | 0.69 | 0.01 | 0.12 | 0.01 | 0.87 | 1556 | 0.67 | -0.06 | 0.13 | 0.06 | 0.84 |
| **All** | **4932** | **0.80** | **-0.33** | **0.98** | **0.00** | **6.87** | **4932** | **0.81** | **0.03** | **0.13** | **0.00** | **0.99** | **4932** | **0.79** | **-0.03** | **0.13** | **0.00** | **0.95** |

A graph with different colored lines

Description automatically generated

Figure 2: APU curves and the corresponding 95% confidence intervals (dashed contours) for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from LS **over forested sites** compared to APU curves for the corresponding estimates from S2. Dashed grey lines bound target user requirements.

A graph of different colored lines

Description automatically generated

Figure 3: APU curves and the corresponding 95% confidence intervals (dashed contours) for SL2P-CCRS estimates of LAI, fCOVER and fAPAR obtained from LS **over unforested sites** compared to APU curves for the corresponding estimates from S2. Dashed grey lines bound target user requirements.

Appendix E

Table 1: Class specific statistics between SL2P-CCRS estimates from LS data versus the corresponding estimates from S2 data (reference), conjointly with the samples size and the variation range of estimates from S2

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **LAI** | | | | | | **fCOVER** | | | | | | **fAPAR** | | | | | |
| **NLCD** | **N** | **R2** | **A** | **U** | **min** | **max** | **N** | **R2** | **A** | **U** | **min** | **max** | **N** | **R2** | **A** | **U** | **min** | **max** |
| EHW | 784 | 0.76 | 0.03 | 0.3 | 0.01 | 3.9 | 785 | 0.74 | 0.02 | 0.08 | 0 | 0.8 | 786 | 0.71 | 0.02 | 0.08 | 0.01 | 0.78 |
| SH | 464 | 0.8 | 0.01 | 0.17 | 0.17 | 2.65 | 464 | 0.85 | 0.04 | 0.06 | 0.1 | 0.68 | 464 | 0.83 | 0.04 | 0.06 | 0.12 | 0.66 |
| CC | 1169 | 0.91 | 0.07 | 0.38 | 0 | 6.92 | 1078 | 0.94 | 0.02 | 0.07 | 0 | 0.98 | 1312 | 0.95 | 0.03 | 0.07 | 0 | 0.95 |
| PH | 873 | 0.89 | -0.01 | 0.37 | 0.02 | 6.64 | 874 | 0.89 | 0.01 | 0.07 | 0 | 0.95 | 876 | 0.89 | 0.01 | 0.07 | 0.01 | 0.93 |
| SS | 8240 | 0.92 | 0.15 | 0.27 | 0 | 7.4 | 7601 | 0.95 | -0.01 | 0.04 | 0 | 0.98 | 7649 | 0.93 | 0 | 0.05 | 0 | 0.97 |
| GH | 8117 | 0.9 | 0.14 | 0.29 | 0 | 5.6 | 8147 | 0.93 | 0.02 | 0.06 | 0 | 0.94 | 8907 | 0.93 | 0.03 | 0.06 | 0 | 0.91 |
| WW | 3245 | 0.82 | -0.22 | 0.61 | 0.02 | 6.39 | 3246 | 0.88 | -0.02 | 0.07 | 0.03 | 0.96 | 3246 | 0.88 | -0.02 | 0.08 | 0.02 | 0.93 |
| MF | 2053 | 0.81 | -0.13 | 0.56 | 0.17 | 6.09 | 2053 | 0.86 | -0.03 | 0.08 | 0.1 | 0.96 | 2053 | 0.84 | -0.04 | 0.09 | 0.1 | 0.93 |
| DF | 10043 | 0.87 | -0.34 | 0.8 | 0.02 | 7.59 | 10050 | 0.92 | -0.03 | 0.08 | 0.01 | 1.01 | 10051 | 0.92 | -0.03 | 0.08 | 0 | 0.98 |
| EF | 11805 | 0.83 | -0.1 | 0.38 | 0 | 5.37 | 11801 | 0.86 | -0.04 | 0.08 | 0 | 0.93 | 11807 | 0.85 | -0.04 | 0.08 | 0.01 | 0.9 |
| **All** | **46793** | **0.89** | **-0.07** | **0.5** | **0.02** | **6.39** | **46099** | **0.93** | **-0.01** | **0.07** | **0.03** | **0.96** | **47151** | **0.92** | **-0.01** | **0.07** | **0.02** | **0.93** |