*Satellite-based Sun-Induced Chlorophyll Fluorescence in
the Greater Alpine Space: Spatial Patterns and Relationship
to Gross Primary Productivity*

Ulisse Gomasca

Leopold-Franzens-Universität Innsbruck
Faculty of Biology

Master Thesis in Ecology & Biodiversity

Supervisor: Mag. Dr. Univ.-Doz., Associate Professor Georg Wohlfahrt

*Department of Ecology
Research Unit Ecosystem Research and Landscape Ecology
Research Group Biometeorology*

Acknowledgements

I would first like to greatly thank my supervisor and mentor, assoc. Prof. Dr. Georg Wohlfahrt, for always being available and supportive in the time of needs throughout the whole period of the thesis. I thank Dr. Karolina Sakowska for the useful introduction to the general topic of research, and MSc Sebastian Gstir for the huge help provided with the programming of several analysis steps.

I would like to thank Dr. Gregory Duveiller and Dr. Alessandro Cescatti for the downscaled SIF product provided as basis for our analysis, Priv.-Doz. Dr. Erich Tasser for providing the Alpine mask, and Dr. Lukas Hörtnagl for the useful insight and information on the CH-Oe2 GPP site.

This work used eddy covariance data acquired and shared by the FLUXNET community, including these networks: AmeriFlux, AfriFlux, AsiaFlux, CarboAfrica, CarboEuropeIP, CarboItaly, CarboMont, ChinaFlux, Fluxnet-Canada, GreenGrass, ICOS, KoFlux, LBA, NECC, OzFlux-TERN, TCOS-Siberia, and USCCC. The ERA-Interim reanalysis data are provided by ECMWF and processed by LSCE. The FLUXNET eddy covariance data processing and harmonization was carried out by the European Fluxes Database Cluster, AmeriFlux Management Project, and Fluxdata project of FLUXNET, with the support of CDIAC and ICOS Ecosystem Thematic Center, and the OzFlux, ChinaFlux and AsiaFlux offices.

Finally, I would like to express my gratitude to my parents for making my academic career possible, and to my girlfriend Chiara for supporting me throughout my entire master study.

Table of Contents

Acknowledgements	II
Table of Contents	III
List of Figures and Tables	IV
Abbreviations	V
Abstract	VI
Zusammenfassung.....	VII
1. Introduction.....	1
2. Materials and Methods	5
2.1. SIF Data Processing	6
2.2. Land Cover Processing and Upscaling	6
2.3. Elevation Extraction and Upscaling	9
2.4. Phenology Fitting Algorithm.....	10
2.5. GPP Extraction.....	11
3. Results	13
3.1. Spatial patterns in GOME-2 downscaled SIF	13
3.2. Land Cover and resulting Temporal Trends	16
3.2.1. Land Cover Extraction	16
3.2.2. SIF Temporal Trends over Land Cover Classes	21
3.3. Elevation and its Relationships with Land Cover	23
3.4. Phenology.....	25
3.5. SIF-GPP Relationship	28
4. Discussion	34
4.1. SIF	34
4.2. Land Cover.....	35
4.3. Elevation.....	37
4.4. Phenology.....	37
4.5. SIF-GPP Relationship	38
4.6. Outlook.....	39
5. Conclusions.....	41
6. Literature	42
Supplementary Material.....	VIII
Declaration of Academic Honesty	X

List of Figures and Tables

Figure 1 – Study Region.....	5
Figure 2 – Downscaled SIF dataset.....	6
Figure 3 – Curve Fitting for Land Phenology Metrics.....	11
Figure 4 – SIF over the Alps.....	14
Figure 5 – Spatial Gaps Statistics.....	14
Figure 6 – Temporal Data Coverage.....	15
Figure 7 – LCC Boxplot.....	16
Figure 8 – Number of LCC per pixel.....	17
Figure 9 – LCC and Dominant-LCC approach.....	19
Figure 10 – Most Frequent Combinations of LCC.....	19
Figure 11 – Scatterplots SIF vs LCC.....	20
Figure 12 – SIF for LCC at Increasing Quantiles.....	21
Figure 13 – Seasonal SIF over LCC.....	22
Figure 14 – Interannual SIF variation over LCC.....	23
Figure 15 – Elevation.....	24
Figure 16 – Dominant-LCC vs Elevation.....	24
Figure 17 – Most Frequent Combinations of LCC vs Elevation.....	25
Figure 18 – Land Phenology Metrics over LCC.....	26
Figure 19 – EC-flux towers sites.....	30
Figure 20 – SIF vs GPP over time.....	30
Figure 21 – SIF vs GPP at the CH-Oe2 site.....	31
Figure 22 – SIF-GPP relationship.....	32
Table 1 – Land Cover Classes.....	7
Table 2 – Fluxnet sites across the Alps.....	12
Table 3 – LCC Extraction Comparison.....	20
Table 4 – Land Phenology Metrics.....	27
Table 5 – Statistics for the SIF-GPP linear regression model.....	33
Table 6 – Z-test for the SIF-GPP relationship.....	33
Table 7 – Statistics for the SIF-LCC Quantiles.....	VIII

Abbreviations

APAR = Absorbed Photosynthetically Active Radiation

DOY = Day Of Year

EC = Eddy-Covariance

ENF = Evergreen Needle Forest

EOS = End Of Season

FLEX = FLuorescence EXplorer

GOME-2 = Global Ozone Monitoring Experiment 2

GPP = Gross Primary Productivity

LCC = Land Cover Classes

MOB = Mid Of Brown-down

MOG = Mid Of Greenup

NPQ = Non-Photochemical Quenching

OCO-2 = Orbiting Carbon Observatory 2

PAR = Photosynthetically Active Radiation

POS = Peak Of Season

SIF = Sun-Induced chlorophyll Fluorescence

SOS = Start Of Season

TROPOMI = TROPOspheric Monitoring Instrument

Abstract

Accurate estimation of terrestrial gross primary productivity is essential for the development of credible future carbon cycle and climate simulations. Current remote sensing techniques allow retrieval of sun-induced chlorophyll fluorescence (SIF) as a proxy for GPP, but low resolution, sparse coverage, or resolution mismatches between different satellite sensors hinder our ability to effectively link SIF to many environmental variables at fine scales. In order to better characterize heterogeneous landscapes, several attempts to downscale SIF products to higher resolutions have been made. We investigate the ability of the downscaled GOME-2 product developed by Duveiller et al. (2019, [1]), to capture the differences in spatiotemporal dynamics over the Greater Alpine Space. We analyse SIF with respect to land cover and elevation and calculate land phenology metrics based on seasonal SIF time series. Ground-based GPP validation suggests biome-specific SIF-GPP relationships, but the comparison was hindered by the resolution mismatch of the data. Moreover, missing data are present at high elevations, diminishing the suitability of current SIF products to analyse cloud-prone mountainous areas. Important insights into spatial patterns and seasonal trends could be inferred at forest and other dominant land cover types, typical of mid elevations in the Alps, but many anthropogenic habitats at low elevations, as well as high elevation grasslands and other small-scale heterogeneous environments could not be thoroughly investigated and are likely to be underrepresented or prone to biases. Similar downscaling procedures might be applied at finer scales to e.g. TROPOMI products, or alternative advanced remote sensing SIF techniques and instruments might be needed in order to enable detailed and systematic evaluations of the Alpine region or similar highly heterogeneous landscapes, before a process-oriented monitoring and unbiased implementation into climate models may be performed.

Zusammenfassung

Eine genaue Schätzung der terrestrischen Brutto-Primärproduktivität ist für die Entwicklung glaubwürdiger zukünftiger Kohlenstoffkreislauf- und Klimasimulationen unerlässlich. Die derzeitigen Fernerkundungstechniken ermöglichen die Erfassung der sonneninduzierten Chlorophyllfluoreszenz (SIF bzw. „Sun-Induced chlorophyll Fluorescence“) als Proxy für die GPP, aber geringe Auflösung, spärliche Abdeckung oder Auflösungsunterschiede zwischen verschiedenen Satellitensensoren behindern unsere Fähigkeit, SIF mit vielen Umweltvariablen auf feinen Skalen effektiv zu verknüpfen. Um heterogene Landschaften besser charakterisieren zu können, wurden mehrere Versuche unternommen, SIF-Produkte auf höhere Auflösungen herunterzurechnen. Wir untersuchen die Fähigkeit des von Duveiller et al. (2019, [1]) entwickelten, herunterskalierten GOME-2-Produkts, die Unterschiede in der raum-zeitlichen Dynamik über den Großen Alpenraum zu erfassen. Wir analysieren das SIF in Bezug auf Landnutzung und Höhe und berechnen Landphänologie-Messgrößen basierend auf saisonalen SIF-Zeitreihen. Die bodengestützte GPP-Validierung lässt auf Biom-spezifische SIF-GPP-Beziehungen schließen, aber der Vergleich wurde durch die Auflösungsinkongruenz der Daten erschwert. Darüber hinaus sind fehlende Daten in großen Höhen vorhanden, was die Eignung der aktuellen SIF-Produkte zur Analyse wolkenanfälliger Berggebiete beeinträchtigt. Wichtige Einblicke in räumliche Muster und saisonale Trends konnten bei Wald- und anderen dominanten Landnutzungstypen, die für mittlere Höhenlagen in den Alpen typisch sind, gewonnen werden, aber viele anthropogene Lebensräume in niedrigen Höhenlagen sowie Hochlandgrasland und andere kleinräumige heterogene Landschaften konnten nicht gründlich untersucht werden und sind wahrscheinlich unterrepräsentiert oder anfällig für Bias. Ähnliche Downscaling-Verfahren könnten in feineren Skalen z.B. auf TROPOMI-Produkte angewandt werden, oder es könnten alternative fortschrittliche Fernerkundungstechniken und -instrumente für SIF benötigt werden, um detaillierte und systematische Bewertungen des Alpenraums oder ähnlicher stark heterogener Landschaften zu ermöglichen, bevor ein prozessorientiertes Monitoring und eine unvoreingenommene Umsetzung in Klimamodelle durchgeführt werden kann.

1. Introduction

Gross photosynthetic CO₂ assimilation from terrestrial ecosystems is the major land carbon sink ([2]), but our ability to predict its magnitude and potential to buffer anthropogenic emissions remains limited. Current gross primary productivity (GPP) estimates usually rely on algorithms and models that integrate data-driven and modelling approaches to ground-based data from eddy-covariance (EC) flux tower stations, and remote sensing of vegetation indices or biometeorological explanatory parameters. However, these methods are constrained by the lack of spatial coverage of the sparsely located EC flux towers with small footprint sizes, not easily scalable beyond the canopy or landscape level ([3], [4]), by the limited response of greenness (reflectance-based) indices to the actual physiological status of the plants ([5], [6], [7], [8]), or by differences in modelling approaches of biometeorological ancillary data, all of which results in high model-to-model variation and uncertainty in GPP estimates ([2], [9], [10], [11]).

Monitoring of the global carbon budget and its implementation into simulation models for future climate scenarios is mandatory and models that can accurately estimate the terrestrial GPP fluxes and that can be linked to the physiological status of the canopy are thus paramount.

More recently, measurements of far-red sun-induced chlorophyll fluorescence (SIF) at acceptable spatial and temporal resolution have become available thanks to advances in remote sensing.

SIF is a portion of the incoming light that is re-emitted at longer wavelengths (660–850 nm) by the photosynthetic apparatus, specifically, by chlorophyll *a* molecules, nanoseconds after absorption of photons as a form of energy dissipation. Both photosynthesis and chlorophyll fluorescence are linked to the light use efficiency model ([12]), since the two processes compete for the same excitation energy, and SIF can thus be used to derive information on the actual photosynthetic activity of the plant and has been applied as a proxy for GPP in the monitoring of photosynthesis at the landscape, regional, and global scale ([13], [14], [15]).

Many studies have shown the capability of predicting photosynthetic yields through remotely sensed passive SIF measurements, which generally correlate well with measurement-based GPP estimates ([13], [2], [16]). In this regard, several studies suggested that the relationship between SIF and GPP might be biome-specific ([17],

[18], [19], [20], [21]), but the question whether a universal relationship might exist still remains ([16], [22]). Furthermore, SIF-based monitoring has the potential for early physiological stress detection, in the form of water or temperature stress ([6], [23]) and for an overall deeper understanding of ecosystem carbon dynamics ([13], [24]).

Despite substantial improvements in satellite resolution and retrieval algorithms, a long-term, fine-resolution global coverage map remains elusive ([25]), and SIF monitoring at the landscape level is still challenging. Since none of the current satellite instruments were specifically designed for SIF retrievals, but rather for cloud detection ([26]), and to account for scattering effects in the atmosphere ([27]), SIF only became available as a fortuitous by-product, and design parameters are not optimized for its measurement, resulting in coarse spatiotemporal resolution. Consequently, numerous mismatches and constraints in resolution, retrieval algorithms, as well as sensor degradation ([25]), hinder our ability to apply SIF to long-term trend and fine-scale analysis. In particular, most ecosystems become highly heterogeneous at scales above 5-10 km ([28]), hindering plausible analysis through continuous coverage SIF measurements such as those provided by the Global Ozone Monitoring Experiment mission (GOME), its successor GOME-2 onboard MetOp-A, and the SCanning Imaging Absorption SpectroMeter for Atmospheric CHartographY (SCIAMACHY), which would otherwise produce a global dataset of remotely sensed SIF data from 1995 up to the present time ([25]).

To tackle this problem, several secondary semi-empirical SIF products that rely on measurement data as well as modelled estimates based on explanatory and ancillary parameters have recently been developed, typically with $0.05^\circ \times 0.05^\circ$ spatial resolution and 8-days temporal resolution. These products show good correlation to the primary products or to GPP estimates at large scales ([28], [29], [30], [31], [32], [33]), however, the question remains whether such products can efficiently account for every biome across the globe, or whether a 0.05° spatial aggregation does still not suffice to accurately monitor fine-scale differences at the ecosystem scale.

High latitude and high elevation environments are thought to be similarly susceptible to increasing temperatures and other climatic changes. Several studies have shown that high-latitude ecosystems have increased their productivity with higher temperatures ([34], [35], [36]), but the same factor can also produce higher stress levels for the plants, ultimately reducing carbon intake ([37]). Such contradictory results challenge the understanding and prediction of ecosystem carbon exchange in a warming climate,

additionally complicated by pervasive cloudiness, shadow contamination, snow cover and open water surfaces typical of the high latitudes ([24]). We hypothesize that similar challenges might be faced when analysing high elevation mountainous areas.

In fact, mountainous and alpine ecosystems are particularly susceptible to climatic changes and to warming conditions, and they can currently be studied as large-scale laboratories of advanced-stage climatic repercussions and feedbacks, which in the future might affect a broader range of ecosystems. The Alps region has been extensively studied by many authors in several research sectors connected to climate change, and represent the ideal setting for analysis of trends in vegetation and carbon fluxes of highly responsive environments, whose consequences and mechanics are still under investigation ([38], [39], [40], [41], [42]). For the aforementioned reasons, reliable indicators for the monitoring of such and similar ecosystems are necessary. However, as raw SIF products still lack the spatiotemporal resolution or the coverage needed for comparison with finely scaled environments, the use of secondary modelled products might become a valid alternative.

SIF-based studies on ecosystem productivity have been conducted for several habitat types, ranging from crop and grassland, to boreal evergreen needle forests and temperate forests ([19], [43], [44]), but, to our knowledge, no European alpine ecosystem has ever been extensively analysed through remotely sensed chlorophyll fluorescence data, and the need for studies on the relationship between SIF and GPP in several biomes remains ([44]).

The overarching aim of this study is to evaluate the ability of current SIF products to monitor GPP at the ecosystem scale in the Alps. In particular, we focus on the GOME-2 downscaled SIF product developed by Duveiller et al. (2019, [1]), in order to assess its suitability in the monitoring of such a highly heterogeneous environment.

We investigate SIF spatial patterns and temporal trends over the Greater Alpine Space, as well as its link to land cover and elevation. We calculate the land phenology metrics over different land cover types and elevation ranges and use those as indicators to evaluate differences in habitat types.

We conduct a direct comparison between SIF and measurement-based GPP estimates from Eddy-Covariance flux tower stations across and in proximity of the Alps, with focus on potential differences in the SIF-to-GPP relationship between different land cover types, examining the possibility of a biome-specific *versus* unique relationship.

Finally, we discuss what conclusions can be drawn from similar studies, as well as outlining the limitations that still remain in the datasets and retrieval methods currently available.

We hypothesise that (i) current SIF products still lack the resolution needed to appreciate the fine scale dynamics of highly heterogenous ecosystems; (ii) the SIF-GPP relationship might indeed be biome-specific at the landscape scale; and that (iii) land cover and elevation play pivotal roles in determining spatiotemporal patterns of SIF across mountainous ecosystems.

2. Materials and Methods

The Greater Alpine Space was selected as study region (gray shading in Figure 1), and data were extracted accordingly, from continental maps or from datasets contained between 43° and 49° N, and 4° and 18° E (red box in Figure 1).

For SIF data, available timestamps covered the period from 2007 to 2017. The 2012 Corine Land Cover product with 2011-2012 temporal extent was used, while the elevation map product is based on data from 2011, and GPP data were extracted from the FLUXNET2015 Dataset, covering different temporal windows between 1997 and 2014, depending on the site.

All analyses were written in and conducted with Matlab (2018b, Mathworks, USA) and the corresponding scripts are available from the corresponding author upon reasonable request.

For SIF data, the downscaled product with resolution 0.05° x 0.05° developed by and described in Duveiller et al. (2019, [1]) was supplied by G. Duveiller (JRC Ispra) on 20.12.2018. The mask for the alpine region was developed on the basis of a shape file provided by E. Tasser (EURAC, Italy). Land cover and elevation data were obtained from the Copernicus database (<https://land.copernicus.eu/>) and modified to match SIF data resolution. For GPP validation, the Fluxnet2015 dataset for sites placed within or in proximity of the Alps was utilized (<https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/>).

Figure 1 – Study Region.

Map of Europe (blue) and region of interest (red) around the study area (Alps: grey shading).

2.1. SIF Data Processing

The SIF dataset derived from the GOME-2 mission is provided with 0.5° spatial resolution. We used the downscaled product developed by Duveiller et al., 2019, which utilizes a light use efficiency modelling approach that is based on various explanatory variables at higher spatial resolution in order to establish a link with SIF. The resulting downscaled SIF product has a 0.05° x 0.05° spatial resolution over 8 days aggregation intervals, and shows high spatiotemporal agreement with SIF retrievals from the TROPospheric Monitoring Instrument (TROPOMI) mission ([1]).

The provided data were trimmed to fall within the Alpine boundaries (Figure 2); and explorative statistics in the form of evaluation of missing data (gap statistics) were conducted on the dataset. Data were grouped over single pixels or over single timestamps, and the resulting spatial and temporal coverage, respectively, was evaluated.

Figure 2 – Downscaled SIF dataset.

Downscaled GOME-2 SIF imported data over region of interest, and Alps mask (gray overlay).

2.2. Land Cover Processing and Upscaling

Extracted Land Cover data were upscaled to match the resolution and coordinates of the downscaled GOME-2 SIF product. However, the categorical nature of habitat type data rendered the process less linear, as no upscaling through simple averaging was possible. CORINE Land Cover (CLC) types were first combined into eleven here-defined “land cover classes” (LCC), thought to be most meaningful for the Alpine region, as described in Table 1. Habitat types were grouped based on similarity, function, and/or

frequency, as some types were very rare or did not occur within the Alps (e.g.: “sea and ocean”), while others covered similar vegetation functional groups (e.g.: permanent crops), or similarly vegetation-free areas (e.g.: glaciers and perpetual snow, bare rocks, sparsely vegetated areas, etc.).

Consequently, the fine resolution (100 m x 100 m) land cover classes data were converted into “fractions” of the lower resolution SIF-derived 0.05° x 0.05° pixel surface areas, assigning a value between 0 and 1 to each land cover class within each pixel of the grid, which corresponds to the relative area covered by each class within the corresponding pixel.

Table 1 – Land Cover Classes.

Eleven Land Cover classes defined in this study, and corresponding land cover types with codes from the Corine Land Cover coding system.

Land Cover Class (LCC)	Corine Land Cover (LABEL3)	CLC code
Artificial	Continuous urban fabric	111
	Discontinuous urban fabric	112
	Industrial or commercial units	121
	Road and rail networks and associated land	122
	Port areas	123
	Airports	124
	Mineral extraction sites	131
	Dump sites	132
	Construction sites	133
	Green urban areas	141
	Sport and leisure facilities	142
Temporary crops (TempCrops)	Non-irrigated arable land	211
	Permanently irrigated land	212
	Rice fields	213
Permanent crops (PermCrops)	Vineyards	221
	Fruit trees and berry plantations	222
	Olive groves	223
Pastures	Pastures	231
Mixed crops (MixedCrops)	Annual crops associated with permanent crops	241
	Complex cultivation patterns	242
	Land principally occupied by agriculture	243
	Agro-forestry areas	244
Broadleaves	Broad-leaved forest	311
Conifers	Coniferous forest	312
Mixed forests	Mixed forest	313

Grasslands	Natural grasslands	321
	Moors and heathland	322
	Sclerophyllous vegetation	323
	Transitional woodland-shrub	324
Glaciers	Beaches	331
	Bare rocks	332
	Sparsely vegetated areas	333
	Burnt areas	334
	Glaciers and perpetual snow	335
Water	Inland marshes	411
	Peat bogs	412
	Salt marshes	421
	Salines	422
	Intertidal flats	423
	Water courses	511
	Water bodies	512
	Coastal lagoons	521
	Estuaries	522
	Sea and ocean	523

A subsample of LCC fractions data that would allow further evaluation devoid of “contamination” from countless habitat types was extracted via two different approaches. This contamination is produced by the high amount of low-area habitat types, characteristic of the heterogeneous landscape in the study region and in particular of the processed dataset, so that even after grouping of land cover types into classes, a major portion of the low resolution pixels were still composed of many different Land Cover Classes with similarly low relative contributions, which would cause confusing and unreadable results. Relative land cover class contributions within pixels $< 5\%$ (0.05) were excluded from the analysis, yet many low-area fractions still remained. Consequently, two different approaches were tested and evaluated: (i) the “dominant LCC” and (ii) the “most frequent combinations of LCC” approaches, as described in the next two paragraphs.

The “dominant-LCC” approach foresees the exclusion of all the datapoints where no single land cover class reaches a surface coverage of at least half of the surface area within the pixel, i.e. where land cover is a combination of many different habitat types with lower area fractions, among which no single one can be considered representative of the whole pixel. Such pixels contain a wide set of different land cover types (confront

with Figure 8.A in the Results) with little surface area that all contribute to a single SIF value that is the average between numerous signals from different land cover types. This SIF average is thus not informative enough to be mechanistically related to land cover. Conversely, dominant or uniform land cover classes or one-LCC-dominated pixels are instead those where one single land cover class alone covers $\geq 50\%$ of the total pixel area.

Regarding the second approach, labelled “most frequent combinations of LCC”, or simply “combination approach”, land cover class fraction values were rounded to one decimal digit, and non-significant contributions were excluded. The combinations of the resulting set of values, i.e. the pixels with the same combination of values within tolerance for the eleven land cover classes (i.e. ± 0.15 for each of the 11 values), were summarized and the ten most common ones were selected.

In order to investigate its temporal trends, SIF data were grouped seasonally and yearly over each land cover class across the study region. Mean values were calculated for extracted data based on the dominant-LCC approach and for the ten most frequent combinations of land cover classes.

2.3. Elevation Extraction and Upscaling

Elevation data were extracted for the Alps region from the EU-DEM v1.1 product with 25 m x 25 m spatial resolution (<https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1.1?tab=metadata>). Fine-resolution values were upscaled through simple averaging in order to match the $0.05^\circ \times 0.05^\circ$ coarse-resolution pixel grid of the SIF dataset.

For some of the analysis and graphs, the elevation gradient was subdivided into four elevation bands of comparable amplitude, which were thought to best represent the altitudinal zonation that characterizes mountain ecosystems, and the Alps in particular: lowland/montane layer below 1000 m, mountainous/subalpine layer from 1000 to 1800 m, alpine layer between 1800 and 2400 m and nival layer above the 2400 m altitude line.

The altitudinal distribution of dominant land cover classes and combinations of classes was plotted for the extracted data based on the two different land cover extraction approaches.

2.4. Phenology Fitting Algorithm

Land surface phenology metrics were computed through simple mathematical derivatives from fitted SIF curves ([45]). Start, End, and Peak Of Season (SOS, EOS, POS), Mid Of Greenup (MOG), and Mid Of Brown-down (MOB) were calculated based on the fitted curves of extracted SIF data from the dominant-LCC approach only. Extracted SIF data were grouped over each land cover class and over single elevation bands.

Specifically, SIF curves were fitted after Gonsamo et al. ([45]) through non-linear least squares method of the 'fit' function in MATLAB to a double-sigmoidal equation of the form:

$$f(x) = a + \frac{b}{1+\exp(-c(x-d))} - \frac{g}{1+\exp(-h(x-m))} \quad (1)$$

Where $f(x)$ is the observed SIF at day of year (DOY) x . As starting values for the coefficients, the values $a = 0.1$, $b = 1$, $c = 0.05$, $d = 100$, $g = 1$, $h = 0.05$, and $m = 250$ were generally used, but slight variations were applied to specific land cover classes or elevation bands that did not respond well to the general fitting algorithm, especially at high elevations, where less data points and frequent missing data rendered the process more challenging and prone to higher variance and lower goodness of fit.

The derivatives and land surface phenology metrics were calculated based on curve tipping points, as shown in Figure 3: the maximum for $f(x)$ was used to estimate the POS metric; SOS and EOS were calculated based on the first and last peaks of $f''(x)$, respectively; and MOG and MOB reflected the maximum and minimum of $f'(x)$, respectively.

Bootstrapping (1000 iterations) was applied on the extracted SIF data in order to produce simulated datasets that would allow calculation of mean phenological indicators with standard deviation. The curve fitting and land surface phenology metrics algorithms were thus applied on the bootstrapped dataset.

R^2 values were calculated for each group to test the goodness of fit for each curve over the bootstrapped subsets of data over specific land cover classes at specific elevation bands.

Figure 3 – Curve Fitting for Land Phenology Metrics.

Example of an idealized seasonal SIF-based phenological curve with derivatives, from which the appropriate phenological parameters are inferred. Purple: $f(x)$; orange: $f'(x)$; lime: $f''(x)$; blue: $f'''(x)$. Appropriate multiplication factors are applied for better visualisation.

2.5. GPP Extraction

Gross Primary Productivity (GPP) data were taken from the FLUXNET2015 Dataset for the sites Neustift (AT-Neu), Davos (CH-Dav), Lavarone (IT-Lav), Monte Bondone (IT-MBo), Renon (IT-Ren), and Torgnon (IT-Tor) within the Alps, and Laegern (CH-Lae), Oensingen crop (CH-Oe2), and Ispra ABS-IS (IT-Isp) for sites just outside of the Alpine boundaries, which were thought to be still close enough to allow acceptable comparison with local SIF estimates. Of the nine selected flux tower stations, three are located within grassland areas (AT-Neu, IT-MBo, IT-Tor), three are sites within evergreen needleleaf (coniferous) forests (CH-Dav, IT-Lav, IT-Ren), whereas CH-Lae is characterized by mixed forest habitat, CH-Oe2 by crops, and IT-Isp by deciduous broadleaf forests. Further site characteristics are listed in Table 2.

The daily aggregated GPP data from the Daytime partitioning method were used (75 percentile, original variable name in the Fluxnet2015 dataset: GPP_DT_VUT_75), and further averaged to 16 days intervals corresponding to the downscaled GOME-2 product's timestamps (with 8 days overlapping to each side on the previous and next timestamps).

SIF data were extracted from single pixels closest to the site coordinates, where the same land cover class was present as dominant land cover (≥ 50 % area covered).

Elevation differences were taken into consideration and will be discussed later, but were not used as filtering option, as this would result in a detrimental trade-off with the geographical distance to the site.

A linear regression model was applied to evaluate the relationship between SIF and GPP, and trend line coefficients were calculated for each site via first degree polynomials. The Z-test was applied to test for significant differences between the slope coefficients of the regression models at each site ([46]).

Table 2 – Fluxnet sites across the Alps.

Eddy Covariance flux tower measurement stations selected for SIF-GPP comparison.

Site ID	Name	IGBP code	Latitude (° N)	Longitude (° E)
AT-Neu	Neustift	GRA	47.116669	11.31750
CH-Dav	Davos	ENF	46.815333	9.855917
CH-Lae	Laegern	MF	47.478333	8.364389
CH-Oe2	Oensingen crop	CRO	47.286417	7.73375
IT-Isp	Ispra ABC-IS	DBF	45.812643	8.633579
IT-Lav	Lavarone	ENF	45.9562	11.28132
IT-MBo	Monte Bondone	GRA	46.014678	11.045831
IT-Ren	Renon	ENF	46.58686	11.43369
IT-Tor	Torgnon	GRA	45.84444	7.578055

3. Results

3.1. Spatial patterns in GOME-2 downscaled SIF

The extracted values for the Alps were averaged and plotted over the study area in order to investigate its spatial patterns. At the $0.05^\circ \times 0.05^\circ$ spatial resolution of the GOME-2 downscaled SIF dataset ([1]), the larger geographical features are well reflected by the SIF means over the period 2007-2017 (Figure 4). Areas with higher SIF values usually represent the lower elevations at the edges of the Alpine arch, or the main valleys. Conversely, the lower SIF means are mostly located in regions with high elevations, around major glaciers, or represent big lakes. In extreme cases, such as those of the highest massifs in the Western Alps where surface areas are mostly covered by glaciers and other open surfaces with little to no vegetation, the absence of substantial plant cover is mirrored by the lack of SIF data with a sufficient quality to pass the pre-processing filter or downscaling procedure, and thus, are not present in the dataset (white areas within the Alpine boundaries in Figure 4). This is thought to be generally true for SIF data over mountainous areas and big lakes, or during rainy periods, where coarse SIF data might be absent, or the explanatory variables used for the downscaling procedure might contain missing data ([1]).

The quality and availability of the data were first investigated through spatial and temporal gap statistics. Figure 5 shows the difference in data availability between the Alps and the neighbouring regions, whose data temporal coverage is generally much more consistent. It is worth noting that this fact alone might be a major source of uncertainty when analysing heterogeneous landscapes comparable to those of the Alps via low-resolution remote sensing data. Aside from the boundary regions, the main valleys and other lower elevation ranges, many of the inner alpine areas often showcase a temporal data coverage below 60 %, with regions where this value decreases further and even approaches or reaches 0 %, where no data are present. This is to be expected, as high elevations are often obscured by frequent cloud cover, ground snow cover during longer periods of the year, and are generally less rich in vegetation and with lower or shorter vegetation activity. In general, explorative gap statistics suggest that for highly fragmented habitats, varying greatly both in land cover and in elevation, remote sensing of sun-induced chlorophyll fluorescence seems to still lack the resolution needed to ascertain the fine scale spatial and temporal patterns.

Figure 4 – SIF over the Alps.

SIF from downscaled GOME-2 product over the study area, averaged over the entire period of data availability (2007-2017).

Figure 5 – Spatial Gaps Statistics.

Percentage of data temporal coverage over the entire period (2007-2017), and Alps boundary (black outline, including state borders).

Another aspect to consider is the seasonal variation in data availability. As shown in Figure 6, data coverage is excellent throughout the summer, whereas the winter months only show reduced data availability or missing data. As already discussed, this is partly due to the lack of photosynthetic tissues in the vegetation, but also to an increased cloud coverage, snow cover, and overall to a reduced quality of the residual SIF signal. In particular, mean data coverage throughout the study period (2007-2017) is

0 % in December and January, with a slow increase throughout spring, maximum coverage from late June till September (when mean coverage reaches 87-96 %), and a rapid decline during November (Figure 6.B). Overall, the gap statistics show how a wide distribution of missing data for the SIF time series and for a major number of regions within the study area result in a challenging approach to ecosystem analysis via SIF passive measurements on the Greater Alpine Space.

Figure 6 – Temporal Data Coverage.

GOME-2 downsampled SIF data coverage over time. **A)** Time period 2007-2017; year labels refer to the start of the year. **B)** Average data coverage (%) with standard deviation over the year for the period 2007-2017.

3.2. Land Cover and resulting Temporal Trends

3.2.1. Land Cover Extraction

Figure 7 shows the boxplots of the land cover classes' fractions for the upscaled land cover dataset. It is worth noting that due to the nature of the fractional approach to the land cover classes for each pixel, the dataset ends up "inflated" by a factor 11 (equal to the number of land cover classes). For this reason, the boxplot of Figure 7 is to be analysed with caution: the high coverage values represented by the numerous outliers actually describe the more information-heavy datapoints, with the lower fractions being much more frequent, but mostly overlapping and less representative of the average land cover type for each pixel. Fractions below the 0.05 limit were excluded from the analysis, yet a large portion of the data remained dominated by a high number of low-area fractions from numerous different land cover classes. Figure 8 shows the number of different land cover classes within each pixel over the Alps, before the non-significant areas were excluded (Figure 8.A), when 5-6 different land cover classes within single pixels are most frequent. After the exclusion of non-significant values, the most frequent pixel combinations decreased to 3 and 4 LCC per pixel (Figure 8.B).

Figure 7 – LCC Boxplot.

Boxplot with descriptive statistics for the relative contribution of Land Cover Classes within GOME-2 downscaled $0.05^\circ \times 0.05^\circ$ pixels over the total study area (number of pixels $N = 8,514$, in each of which a relative area fraction of each of the 11 land cover classes was represented, making the total number of data $n = 93,654$).

Figure 8 – Number of LCC per pixel.

Number of different land cover classes within single GOME-2 downscaled $0.05^\circ \times 0.05^\circ$ pixels. **A)** Map of study area (most frequent bin = 6, not shown). **B)** Frequencies, after removal of non-significant land cover classes contributions (area within GOME-2 downscaled pixel < 5%).

In order to enable further evaluation of the whole dataset, only a subsample of pixels with high-coverage ($\geq 50\%$ of the pixel) land cover classes were extracted and analysed (dominant-LCC approach). Common combinations of land cover classes within single pixels were also examined, as described in the Methods, but this approach seemed less efficient at covering the diversity of SIF-land cover relationships over the Alps and was not explored in detail.

The selection approach based on uniform land cover classes over pixels resulted in a 47 % data coverage within the study region (Figure 9), whereas the ten most frequent combinations only covered 26 % of the total study area (Figure 10). However, the frequent recurrence of particular sets of land cover classes is thought to be typical for the study area.

It was decided to continue the analysis with the land cover data extracted via the dominant-LCC approach, since the data coverage was higher than via the combination-approach. Some of the land cover classes were in this case often underrepresented, and the few data points rendered statistical processing challenging. For instance, extracted data points for the class “artificial”, comprised of several anthropogenic and urban environments, are only 0.6 % of the grid pixels with fractions above the 5 % of this land cover class. On the other end of the spectrum, the class “glaciers” that includes glaciers and other natural rocky or open surfaces with little to no vegetation was represented by dominant fractions within pixels in 26.9 % of the cases. This underrepresentation of significant fractions of land cover classes within $0.05^\circ \times 0.05^\circ$ grid pixels is particularly relevant for all the anthropogenic land cover classes (temporary crops: 9.5 %, permanent crops: 5.6 %, pastures: 3.5 %, mixed crops: 1.8 %), whereas typical alpine habitats were extracted in a more satisfactory way (broadleaf forests: 16.7 %,

evergreen forests: 21.6 %, mixed forests: 6.7 %, grassland and shrubs ecosystems: 11.9 %), and water bodies again only to the 8.9 %.

However, the same is true for the ten most common combinations of land cover classes found within the grid of low-resolution $0.05^\circ \times 0.05^\circ$ pixels. In fact, such combinations mostly include mid to high elevation habitat types such as coniferous forests, alpine grasslands and glaciers, with some of the combinations even overlapping in their land cover class contributions and elevation ranges (for reference, see Figure 17 in the next section). Moreover, the total surface area (number of pixels) covered by land cover data extracted through the dominant-LCC approach was 47.1 %, whereas the number of pixels covered by the ten most common combinations was only 26.1 %, as already stated. In order to increase the area covered by extracted data up to 50 %, the 30 most common combinations would have to be taken into consideration, which was deemed as overly confusing and was thus not considered further.

The extraction of land cover data where at least 50 % of the pixel area was covered by one single dominant land cover class was preferred also because pixels with comparably similar low-area contributions from very different land cover types result in SIF averages that can bring very little information on the actual correlation to the type of vegetation, as already discussed.

Quantiles of land cover classes' fractions for the cumulative probability from 50 % to 99 % (50-75-90-95-99 %) were extracted, as a mean to estimate the average SIF value over the study period that would result from an increasingly clearer contribution from one single class of land cover types. Figure 11 and Figure 12 show how SIF averages tend towards a value that is deemed to be specific for each land cover class. This can only be observed where the area covered by the specific land cover class tends towards the maximum, whereas at lower coverage, values are scattered more widely (Figure 11), and are thus thought to be less representative of the land cover class' actual SIF average. This does not appear to be true for all the classes, as temporary and permanent crops, in particular, display a much more dispersed arrangement of the data, with seemingly no particular pattern even at high cumulative probability quantiles, which could be caused by the poorer sample size of these particular classes, by differences in phenology, or due to differences in management practices.

It is worth reiterating that this method is statistically not representative of several small-patch land cover areas (refer to Table 3), which could behave differently than large area habitats, as increasing the cumulative probability of the quantile drastically

decreases the number of included pixels. One could even go as far as to say that for most of the land cover classes, what was analysed were in fact the outliers, instead of the norm (see the boxplot in Figure 7). In this case, however, only the higher values, i.e. the higher fractions of land cover classes' covered area within a pixel, are thought to reflect more reasonable SIF estimates for each land cover class, and as such, this process served as an approximation for assessing a possible theoretical SIF value for each class of land cover type within the alpine region, and to examine the differences and limits of a reduced yet specific dataset versus a larger but more ambiguous one.

Figure 9 – LCC and Dominant-LCC approach.

Dominance of single Land Cover classes, i.e. pixels with surface area covered by one single land cover class over 50 % (47 % total coverage). **A)** 11 Land Cover classes. **B)** Total coverage (red) of land cover pixels with one dominant (≥ 50 %) LCC over the alpine region (grey shading).

Figure 10 – Most Frequent Combinations of LCC.

Most frequent combinations of Land Cover classes (26 % total coverage). Combinations: 1 = conifer forests (1); 2 = grassland + glacier + conifers; 3 = conifers + mixed forest; 4 = glaciers + grassland (1); 5 = mostly glaciers; 6 = 100 % glaciers; 7 = glaciers + grassland (2); 8 = conifer forests (2); 9 = conifers + grassland; 10 = conifers + pasture.

Table 3 – Comparison of LCC Extraction Approaches.

Number of extracted pixels via the two approaches: **A-B)** “dominant-LCC” approach; **C)** number of pixels with significant fractions (> 5 % of total pixel area) of area covered by each land cover class (not mutually exclusive); **D-E)** “Most common combinations” approach. The total number of SIF-derived pixels (column C, total) refers to the total number of pixels within the Alps.

A) Land Cover class	B) N° pixels	C) Significant fractions within pixels	D) Combination	E) N° pixels
Artificial	11	1703	Conifer Forests (1)	295
Temporary crops	87	919	Grassland, Glacier, Conifers	266
Permanent crops	13	232	Conifers, Mixed Forest	158
Pastures	114	3294	Glaciers, Grassland (1)	297
Mixed crops	47	2567	Mostly Glaciers	166
Broadleaf forests	490	2927	100% Glaciers	230
Coniferous forests	1315	6075	Glaciers, Grassland (2)	192
Mixed forests	296	4398	Conifer Forests (2)	164
Grass- and shrublands	669	5625	Conifers, Grassland	264
Glaciers	935	3482	Conifers, Pasture	187
Water	34	381	-	-
Total	4011	8514	Total	2219

Figure 11 – Scatterplots SIF vs LCC.

Correlation between SIF and fraction of Land Cover classes, over the 90 % cumulative probability quantile.

Figure 12 – SIF for LCC at Increasing Quantiles.

SIF average values at specific fraction of Land Cover classes, over quantiles for the cumulative probability of 50, 75, 90, 95, and 99 %. Error bars are not shown for clarity: see Table 7 in the Supplementary Material for standard deviation values.

3.2.2. SIF Temporal Trends over Land Cover Classes

A first look at the seasonal variation of SIF over each land cover class is shown in Figure 13. Although a quantitative investigation of the seasonal parameters is addressed below in the “Phenology” section, both the maximum values and the shape of the curves can already give insightful information on some of the characteristics and differences between land cover classes. Curves with higher maxima are those that represent more productive and/or more densely vegetated land cover areas, whereas lower values throughout the season are found in land cover classes such as glaciers and water bodies, as expected, since little to no vegetation is present within these habitat types. More subtle differences can also be seen between, for instance, the differences in summer peaks between broadleaf and needleleaf forests, reflecting the different response of the vegetation to incoming photosynthetically active radiation (PAR), and to potential ecosystem limitations, such as water, nutrient, or temperature constraints. In the case of coniferous and broadleaf forests, the different elevation ranges of the two habitat types needs to be considered, as at higher elevations more limiting environmental conditions are present, which cause a decrease in productivity mainly due to a shorter vegetative period ([47]). Likewise, the shape of the curves can give insight into the timing and speed of green-up and brown-down of the vegetation, with

some classes of land cover types showcasing strong increases in SIF already around the beginning of April (DOY = 100), whereas others only following at later dates.

The short timescales for which SIF measurements from remote-sensing are available make the year-to-year comparison challenging, and possibly of little meaning. Moreover, long-term trend analyses are discouraged due to acknowledged instrument limitations, different SIF retrieval algorithms, or mismatches across sensors. Nonetheless, a difference can be observed between the yearly SIF means before and after 2013 (Figure 14), but this can only hint towards potential year-to-year differences that should be taken as purely thought-provoking. In particular, starting from 2014, the average SIF values for the Alpine region seem to be lower than in previous years. This substantial systematic difference is likely due to the change of instrument resolution of the GOME-2 mission from 40 km x 80 km before July 2013, and 40 km x 40 km footprint sizes after that date ([15], [48]), or to other biases in the dataset, such as calibration drift of the GOME-2 instruments, a known issue of instrument degradation responsible for a decrease in sun-induced chlorophyll fluorescence estimates (https://avdc.gsfc.nasa.gov/pub/data/satellite/MetOp/GOME_F/README_GOME-F_v26-v27.pdf GOME-2 FLOURESCENCE README FILE), or to environmental conditions that were not accounted for in this study.

Figure 13 – Seasonal SIF over LCC.

Seasonal SIF means for areas with uniform land cover classes (coverage $\geq 50\%$).

Figure 14 – Interannual SIF variation over LCC.

Interannual mean SIF variability for areas with uniform land cover classes (coverage $\geq 50\%$).

3.3. Elevation and its Relationships with Land Cover

Numerical elevation data were upscaled via simple averaging of high-resolution 25 m x 25 m data into the $0.05^\circ \times 0.05^\circ$ data grid matching SIF and extracted land cover fractions (Figure 15.A). For the purpose of easier comparison with SIF and land cover, elevation gradient data were divided into elevation bands that should approximate the average altitudinal zonation of the Alps. The aim was to reflect the major changes in the distribution of the vegetation over the altitudinal gradient (Figure 15.B), but a simplification was paramount, since no definitive zonation can be defined across changing latitude and exposition.

Figure 16 nicely calls back to the altitudinal zonation of land cover types, with all the artificial or anthropogenic habitats on the lower elevation bands, broadleaf forests with their peak in coverage in the lower mountainous level, followed by mixed forests and evergreen forests reaching up to the subalpine level, which is then replaced by the grassland ecosystems and finally glaciers. The same zonation is reflected in the combinations of land cover classes depicted in Figure 17, although not as clearly (for the altitudinal zonation see [49], [50]).

Figure 15 – Elevation.

Upscaled elevation map with averaged values over the area of GOME-2 downscaled $0.05^\circ \times 0.05^\circ$ pixels. **A)** Average values over pixels. **B)** Elevation bands: light green = 0-1000 m; dark green = 1000-1800 m; dark blue = 1800-2400 m; light blue = 2400-3649.1 m.

Figure 16 – Dominant-LCC vs Elevation.

Number of pixels with dominant coverage for each land cover class at different elevations.

Figure 17 – Most Frequent Combinations of LCC vs Elevation.

Number of pixels for 10 most common combinations of land cover classes at different elevations.

3.4. Phenology

Phenological indicators were calculated over a bootstrapped dataset for each land cover class, at each elevation band where sufficient data were present for the specific class. As expected, data groups with low sample size resulted in very high standard deviation and thus need to be compared with caution to other values. In particular, the higher elevation bands turned out particularly challenging, even when treated with customised fitting algorithms. This is reflected in the gap statistics, which already highlighted the low availability of data at high elevations. Sample bar graphs for Start Of Season (SOS), End Of Season (EOS) and Peak Of Season (POS) are shown in Figure 18, whereas the complete phenological estimates are found in Table 4.

The mean day of the year (DOY) calculated for the SOS, MOG (Mid Of Greenup), and POS shifts to later dates at higher elevation for most of the land cover classes, whereas the opposite can be said for MOB (Mid Of Brown-down) and EOS, as expected. Some exceptions were found, where phenology did not shift with elevation: for instance, conifers or pastures showcase earlier SOS at mid elevations (between 1000 m and 1800 m) than at lower altitude. However, this land cover classes are thought to be adapted to mid elevations and have their optimum range in the mountainous or alpine layer, rather than at the lowest elevation band, which could explain the earlier dates at the mid elevation band. EOS is overall much more conservative, i.e. tends to shift less depending on elevation.

Figure 18 – Land Phenology Metrics over LCC.

DOY of phenological indicators with standard deviation over bootstrapped data (1000 iterations) for each land cover class at each elevation band where data are present. **A)** Start Of Season (SOS); **B)** Peak Of Season (POS); **C)** End Of Season (EOS).

Table 4 – Land Phenology Metrics.

Phenological parameters for each land cover class (A-K) within specific elevation bands (a-d). Differences between elevation bands of the same land cover class are all significant at $\alpha = 0.05$. R^2 refers to the curve fitting.

	Artificial (A)	Temporary Crops (B)	Permanent Crops (C)	Pastures (D)		Mixed Crops (E)	
	0-1000 m (a)	0-1000 m (a)	0-1000 m (a)	0-1000 m (a)	1000-1800 m (b)	0-1000 m (a)	1000-1800 m (b)
SOS	52.53 ± 4.89	53.12 ± 2.79	50.77 ± 10.77	60.17 ± 2.17	55.47 ± 3.16	51.8 ± 3.13	69.43 ± 3.16
MOG	106.33 ± 1.87	98.86 ± 1.16	110.03 ± 2.88	101.35 ± 0.97	104.15 ± 1.3	104.25 ± 1.47	115.37 ± 1.23
POS	173.58 ± 1.63	169.73 ± 1.58	172.4 ± 1.87	169.61 ± 1.56	173.86 ± 1.46	173.92 ± 1.4	166.59 ± 1.42
MOB	262.39 ± 2.4	262.78 ± 2.11	252.32 ± 4.77	267.04 ± 2.11	266.05 ± 3.43	258.57 ± 1.78	246.16 ± 5.25
EOS	344.39 ± 10.37	328.4 ± 7.07	348.44 ± 12.04	331.35 ± 6.45	336.59 ± 7.72	328.76 ± 6.1	362.34 ± 4.09
R ²	1 ± 0	1 ± 0	1 ± 0	1 ± 0	1 ± 0	1 ± 0	1 ± 0
	Broadleaves Forests (F)		Coniferous Forests (G)		Mixed Forests (H)		
	0-1000 m (a)	1000-1800 m (b)	0-1000 m (a)	1000-1800 m (b)	0-1000 m (a)	1000-1800 m (b)	
SOS	78.99 ± 1.56	88.11 ± 4.61	64.27 ± 2.34	62.42 ± 2.66	74.61 ± 2.19	80.83 ± 3.1	
MOG	119.47 ± 0.99	127.84 ± 2.7	120.23 ± 1.32	132 ± 1.5	120.09 ± 1.11	132.59 ± 1.23	
POS	173.16 ± 1.03	179.93 ± 1.52	178.85 ± 1.13	185.23 ± 1.53	175.99 ± 1.18	183.35 ± 1.16	
MOB	253.16 ± 2.57	251.79 ± 2.96	252.6 ± 3.12	240.81 ± 4.89	241.42 ± 5.89	246.45 ± 2.84	
EOS	329.74 ± 11.02	317.6 ± 11.65	339.11 ± 9.56	318.9 ± 11.06	313.7 ± 12.39	329.39 ± 7.02	
R ²	1 ± 0	1 ± 0.01	1 ± 0	0.99 ± 0	1 ± 0	1 ± 0	
	Grassland and shrubs (I)		Glaciers and open spaces without vegetation (J)		Water bodies (K)		
	0-1000 m (a)	1000-1800 m (b)	1800-2400 m (c)	2400-3650 m (d)	1000-1800 m (b)	1800-2400 m (c)	0-1000 m (a)
SOS	65.66 ± 2.96	74.2 ± 8.83	81.34 ± 27.07	58.32 ± 51.46	59.42 ± 20.35	98.18 ± 2.94	66.17 ± 7.52
MOG	123.12 ± 1.39	139.6 ± 4.2	142.03 ± 16.53	121.36 ± 32.18	138.38 ± 16.42	161.34 ± 1.5	127.88 ± 2.59
POS	175.04 ± 1.09	188.59 ± 2.28	192.17 ± 6.68	195.59 ± 8.98	190.74 ± 4.82	202.05 ± 0.88	183.76 ± 1.77
MOB	236.4 ± 2.76	239.61 ± 2.7	235.5 ± 35.63	226.89 ± 87.91	243.12 ± 7.59	244.07 ± 1.08	249.08 ± 4.8
EOS	335.61 ± 9.68	310.25 ± 5.01	304.24 ± 16.39	319.71 ± 35.57	308.92 ± 13.6	296.82 ± 2.26	338.99 ± 11.71
R ²	1 ± 0	0.99 ± 0.01	0.94 ± 0.09	0.69 ± 0.27	0.95 ± 0.11	0.97 ± 0.01	1 ± 0.02

3.5. SIF-GPP Relationship

GPP data from selected Fluxnet sites across the Alps, or just outside of the Greater Alpine Space, were compared to SIF data in correspondence of the site locations. Since Eddy-Covariance Fluxnet towers have much smaller footprints than that of the downscaled GOME-2 SIF product, the $0.05^\circ \times 0.05^\circ$ pixels with the same dominant land cover class closest to the flux tower sites were used for the comparison. It is worth noting that five out of the nine sites (AT-Neu, IT-Isp, IT-Lav, IT-MBo, and IT-Tor) were positioned at a substantially different elevation (> 300 m difference) from the closest pixel with the same uniform land cover class, thus potentially influencing the SIF comparison through such difference in altitude. Figure 19 shows the location of the Fluxnet Eddy-Covariance towers (“+” symbol), the SIF-derived pixel in which the station is located (“o” symbol), and the closest pixel with the same land cover class that was used for the evaluation (“x” symbol). Overlapping symbols suggest a potential for more solid comparison between GPP and SIF data, whereas sites that are not directly associated with a pixel with the same land cover class at a close distance could result in a drift in the values due to different meso-meteorological and environmental conditions.

GPP data from Eddy Covariance flux tower stations across the Alps were compared to SIF time series in order to evaluate their relationship between 2007 and 2014, where data were available for both datasets. The variation over the season follows similar trends for both SIF and GPP, and the timing of seasonal phenology is often similar, hinting towards the link between the two processes (Figure 20). Note that the axis for SIF and GPP are different, since the two measures were plotted independently from each other and with no further calculation to establish a mechanistical link between the data. Despite similar trends, SIF and GPP curves display appreciable differences in data availability (especially in winter), shape, and maxima of certain years or at specific sites, as well as in the ratio between the absolute values of the two datasets between sites. Some of these differences might be explained by the processing methods utilized: although the SIF data used for the comparison to site GPP were extracted from the closest pixels with the same land cover class, a mismatch both in geographical coordinates and elevation is present for some of the sites, which might influence the outcome of the comparison. For instance, the CH-Oe2 EC-flux tower site is located within an agricultural field managed as a typical intensive 3-year crop rotation under the Swiss Integrated Pest Management regime (IP Suisse). The main crop planted every

three years is winter wheat, followed by winter barley, and a third crop between potato, winter rapeseed or peas ([51]). These plant species all have different sensitivities to environmental parameters, CO₂ uptake rates, and productivity values. Consequently, yearly differences will be present in the modelled GPP dataset: in fact, the substantially lower GPP curve for the year 2010 corresponds to the growing of peas, whose period of carbon uptake was rather short, and peas also showcase very little CO₂ uptake in comparison to other crop species. Conversely, SIF data were subsampled for a crop-dominated region at a much coarser scale with presumably countless differences in management practices and plant species composition. It is thus not surprising that the GPP peak in 2010 shows a much lower maximum than SIF (Figure 21). Moreover, excluding the planting of cover crops every 4 to 6 years, – for instance, this can be seen as a secondary peak at the end of September 2009 – crops at the CH-Oe2 site are generally harvested in July, which explains the drop and subsequent low GPP values, which are not reflected in the SIF curve, since SIF data are an average of a much wider area that does not allow for the identification of such fine scale differences. For more information on the site CH-Oe2 refer to Emmel et al. (2018, [51]). Despite the substantial mismatch in spatial resolution and therefore management practices, the spring transition of GPP and SIF data correlates well, which suggests that SIF is still able to capture at least some of the seasonal variation in productivity of cropland sites.

Similarly, other sites showcase little overlap between SIF and GPP (confront R^2 values in Table 5), as in the case of CH-Dav. However, the sparse nature of either SIF or GPP temporal datapoints hinders an objective comparison of the two parameters. On the contrary, sites with high coefficients of determination (R^2) generally display good data coverage and overlap in GPP and SIF data, with the only exception being the site IT-Isp, where, despite the high R^2 , GPP data are only available for the last two years of the study period (2013-2014). Excluding these sites, SIF seems to capture GPP trends in coniferous forests (evergreen needle forest, ENF) sufficiently well (mean $R^2 = 0.59$) but performs worse at the grassland sites considered (mean $R^2 = 0.52$). However, grassland sites are thought to be influenced by higher noise of mixed SIF signal contributions compared to ENF sites, especially at lower elevations, as for AT-Neu, since grassland patches below the tree line are likely to be managed via different management practices, similar to cropland sites, and also mixed with signals from other land cover types within one SIF pixel, such as urban settlements, crop sites, forests etc. This is true at least for the AT-Neu site, which is located at the bottom of the Stubai valley,

explaining the lower values of explained variability between GPP and SIF. Nonetheless, it is interesting to notice that despite this mixed signal, SIF is able to capture the drop in GPP associated with mowing with surprising efficiency at the AT-Neu site, at least in some years (2007-2010). The only mixed forest site had the best overlap between SIF and GPP among all sites ($R^2 = 0.85$), possibly due to the high availability of datapoints for both datasets.

Figure 19 – EC-flux towers sites.

Site location and approximated position within GOME-2 downscaled SIF 0.05° x 0.05° pixel grid.

Figure 20 – SIF vs GPP over time.

Temporal GPP variation from Fluxnet sites and downscaled GOME-2 SIF from pixels close to the sites and with the same dominant land cover class; blue = SIF; orange = GPP.

Figure 21 – SIF vs GPP at the CH-Oe2 site.

Temporal GPP variation at CH-Oe2 site, and downscaled GOME-2 SIF from the closest pixel within the Alps with dominant land cover class “temporary crops”.

A linear regression model was applied to the relationship between GPP estimates and SIF values at each flux tower site. Graphical results can be found in Figure 22, while statistics are shown in Table 5. It is worth noting that the slope of the trend lines calculated by the linear regression model are significantly different in many if not most of the matchups between sites (Z-test, Table 6). In particular, the three grassland sites (AT-Neu, IT-MBo, and IT-Tor) do not appear to differ significantly, while the Davos EC-flux tower in Switzerland (ENF) shows strong differences to the other two conifer sites (IT-Lav and IT-Ren) that are not easily explained, since the three sites are not affected by a geographical mismatch between SIF and GPP measurement site (Figure 19), the elevation of the three sites is also comparable, and the stronger difference is recorded for the site with closer elevation to CH-Dav. However, this anomaly seems to be specific to the Davos site, as the other two conifers sites do not differ significantly, even if just marginally inside the 95 % confidence interval. Interestingly, CH-Lae, a mixed forest site, shows similarity to the three grassland sites, with a nearly perfect overlapping trend compared to IT-Tor, and to the ENF site at IT-Ren, which could be expected due to the partly similar nature of coniferous and mixed forests. The CH-Oe2 cropland site does only show a significant difference in the slope of the correlation trend line with the IT-Lav conifer site, but the intercept of the line is different by nearly 6 points. In fact, IT-Lav shows an intercept value which is uniquely high, compared to all other sites. It should also be noted that the CH-Oe2 site is particular due to specific management practices

that are not applied equally to the broader area from which the SIF signal is collected, and this mismatch might be the cause of a shift in the GPP-SIF slope. Finally, the only broadleaf forest site at IT-Isp only shows marginally significant similarity to the Neustift (AT-Neu) grassland site, but strong differences with all other sites, in line with expected results based on habitat type and geographical coordinates, since this site is the southernmost one, as well as located just outside of the Alpine region.

Regarding the GPP-SIF relation per-se, the Davos station (CH-Dav) displayed high SIF increase with only marginal GPP increase, whereas at the Ispra site (IT-Isp), GPP increased much faster by growing SIF when compared to other sites. This could be related to elevation or habitat type, as CH-Dav is a high elevation station, while IT-Isp lies just outside of the Alpine space, and thus at much lower altitude (around 210 m a.s.l.) and at lower latitude as well. However, due to the lack of uninterrupted series of data for either GPP or SIF in the period 2007-2014 at these site, the peculiar slope coefficients are more likely to be caused by insufficient data availability.

Figure 22 – SIF-GPP relationship.

Relationship between SIF and GPP data at every flux tower site. Dots: data points; semi-transparent area: data range; black line: trend line after linear regression model; grey lines: standard error of line coefficients; red lines: 95 % prediction interval.

Table 5 – Statistics for the SIF-GPP linear regression model.

Linear regression model statistics for the EC-flux tower sites analysed.

Site	Slope	SE slope	Intercept	SE intercept	df	R2
AT-Neu	11.56	1.47	3.24	0.74	102	0.38
CH-Dav	2.71	0.36	3.51	0.21	132	0.30
CH-Lae	9.57	0.26	0.65	0.23	245	0.85
CH-Oe2	6.59	0.65	-0.07	0.56	257	0.29
IT-Isp	14.83	0.84	0.32	0.54	60	0.84
IT-Lav	7.44	0.57	5.87	0.33	178	0.49
IT-MBo	9.02	0.96	2.84	0.52	113	0.44
IT-Ren	8.90	0.47	2.41	0.31	172	0.68
IT-Tor	9.57	0.49	0.37	0.31	130	0.75

Table 6 – Z-test for the SIF-GPP relationship.

Z-test for the slope coefficients for each combination of two sites. Significant differences at the 95 % confidence interval are marked.

Site	AT-Neu	CH-Dav	CH-Lae	CH-Oe2	IT-Isp	IT-Lav	IT-MBo	IT-Ren	IT-Tor
AT-Neu	--	5.85	1.34	3.10	1.93	2.62	1.45	1.73	1.29
CH-Dav	5.85	--	15.37	5.24	13.26	6.98	6.16	10.50	11.33
CH-Lae	1.34	15.37	--	4.28	5.99	3.38	0.55	1.25	0.00
CH-Oe2	3.10	5.24	4.28	--	7.78	0.99	2.11	2.91	3.69
IT-Isp	1.93	13.26	5.99	7.78	--	7.27	4.56	6.18	5.43
IT-Lav	2.62	6.98	3.38	0.99	7.27	--	1.42	1.98	2.83
IT-MBo	1.45	6.16	0.55	2.11	4.56	1.42	--	0.12	0.51
IT-Ren	1.73	10.50	1.25	2.91	6.18	1.98	0.12	--	0.99
IT-Tor	1.29	11.33	0.00	3.69	5.43	2.83	0.51	0.99	--

4. Discussion

Recent improvements in remote sensing techniques and instruments, retrieval algorithms, and post-processing downscaling procedures that have been developed for the measurement of sun-induced chlorophyll fluorescence from satellites have substantially increased the quality of available data, but a resolution mismatch both in spatial and temporal dimensions with other environmental parameters, such as land cover type or elevation, is still often present. SIF can successfully be implemented as a monitoring tool for ecosystem productivity and plant stress at large scales, where habitats remain somewhat homogenous, and fine-scale differences are minor or can be neglected.

However, differences up to a factor of 2 are still present between SIF products derived from different sensors, or through different retrieval algorithms ([25]). Additionally, more complex ecosystems, such as shown here for the Alps, need a more refined spatial resolution to fully assess landscape to canopy patterns in carbon fluxes and plant productivity at the scale of management units. Furthermore, a longer and unbiased SIF database is needed to allow for meaningful year-to-year or long-term trend analysis, while missing data are present at specific regions, where frequent cloud cover hinders data collection, with the risk of underestimating terrestrial carbon sequestration potential in these regions.

Despite these limitations, numerous useful insights can be gained from downscaled and modelled SIF products that increase the spatial resolution to the 0.05° parcel, and the spatial coverage to nearly global.

4.1. SIF

In our study, SIF data from the GOME-2 downscaled product developed by Duveiller et al. ([1]) were used to analyse the Greater Alpine Space. As shown by the gap-statistics in Figure 6, winter months are characterized by a reduced data availability or lack of data. However, photosynthetic processes in evergreen forests, as well as other stress mechanisms that might increase SIF, are partially active even in winter times ([52], [53]). Usually, an increase in photoprotective pigments associated with non-photochemical quenching (NPQ) occur in concomitance with a decrease in reaction centre proteins, which is related to a general decrease in chlorophyll fluorescence ([54], [55], [56]). However, the exact dynamics and residual SIF signals at large scales are still not fully understood ([24]), and missing data during this period might lead to a potential

underestimation of winter activity of evergreen habitat types. On the contrary, other authors argue that the opposite might be true as well, as SIF is suggested to be related only indirectly to photosynthetic activity, while linearly dependent to absorbed photosynthetically active radiation (APAR), potentially leading to overestimation of plant winter activity where SIF data are present (refer to [24]).

Overall, major gaps in spatial coverage were only found within regions corresponding to the highest elevations, where surfaces are mostly covered by perennial snow, glaciers, or bare rocks, and thus, without vegetation capable of producing a detectable SIF signal. Missing information from such habitat types should therefore not critically affect analysis of SIF, likely approximating zero values even if data were available. More problematic is the lower data availability at mid- to high elevations, where productive habitats such as coniferous forests, shrub communities, alpine grasslands and pastures are present and would need to be accounted for without biases.

Chen et al. (2019, [57]) successfully implemented GOME-2 and OCO-2 SIF data to study productivity and phenology on the Tibetan Plateau, which is a region of alpine ecosystems with high heterogeneity, similar to the Alps, reporting general limitations due to GOME-2 data quality based on measurement instruments, algorithms, and sky conditions, that were thought to be unlikely to influence the results in a major way. However, we argue that some major differences set apart the Tibetan Plateau from our study regions, as the Alps are characterized by frequent cloud cover, intense management and relatively high population density, compared to the Tibetan Plateau. These factors are thought to both increase landscape diversity and decrease data quality, thus resulting in the necessity of higher resolution data to properly assess SIF trends and derived phenology and terrestrial productivity.

4.2. Land Cover

The mismatch in spatial resolution between SIF, land cover, and elevation data can be challenging to face: especially for categorical land cover data, a simple upscaling is not possible, and workarounds need to be found in order to defensibly confront them to SIF measurements. Specifically, the aggregation of land cover pixels at coarser spatial resolution through the extraction of dominant land cover classes resulted in a strong decrease in datapoints available for specific land cover classes (such as anthropogenic habitat types) which are only better represented at finer resolutions due to small patch size, and were thus likely underrepresented in our analysis. In particular, urban

environments, together with other artificial surfaces connected to human activities, and permanent crops, seem to be particularly affected, since these land cover types are usually concentrated in small areas, especially in the Alps, rendering their analysis at coarse spatial scales inappropriate. Despite a slightly larger sample size of extracted dominant pixels, the same could be said for other classes of land cover types, such as that of temporary crops. Moreover, management practices in highly fragmented agricultural areas characteristic of the European Continent tend to drastically increase the differences between differently managed patches of land, so that e.g. a field cultivated with peas will have a much shorter vegetation period and much lower productivity and carbon absorption than a neighbouring field where wheat is grown (as was observed at the CH-Oe2 Fluxnet site in 2009, Figure 21). However, at coarser spatial scales, these differences are averaged into a single SIF signal, which hardly represents the single management practices. In fact, no definitive SIF value characteristic of temporary and permanent crops could be found at higher quantiles, showing a sparsely scattered behaviour of data points, which could be equivalently caused by a lack of sufficient data, or to the different management practices characteristic of different regions. Similarly, however, natural land cover classes with “mixed” plant communities, such as mixed forests or mixed crops, show less tendency towards a single SIF value. It is therefore less likely that they could be mechanistically linked to GPP with a biome-specific approach, and the relationship between spatial resolution, SIF and eventually GPP still needs to be investigated further at these land cover types. The land cover class “grasslands” was defined as containing not only pure grassland, but also shrub communities, and other habitat types (see Table 1 for details), thus likely contaminating the resulting SIF estimate at higher quantiles. The same is true for other land cover classes, since our approach was to group similar land cover types together to reduce the complexity of the analysis and of the interpretation, but other classes did not seem to be affected in this sense.

In regard to land cover, another source of underrepresentation for many habitat types is thought to be the selection process for more informative pixels, described in section 2.2 of the Methods. None of the two selection approaches used to handle land cover data-upscaling was sufficient to cover the majority of the study area, and thus the majority of the region where SIF data were present could not be analysed via land cover type. However, this is primarily due to the intrinsic heterogeneity of the alpine landscape; Guanter et al. (2014, [19]), among others, noted that the coarse resolution

of SIF retrievals at the 0.5° parcel might not be sufficient to properly sample highly fragmented European cropland sites. We think that in regard to the Alps, this is also true for the 0.05° resolution, and that only a reduced mismatch between land cover and SIF data could effectively improve the representation of fine scale land cover dynamics. Other studies aimed at SIF downscaling found a limited contribution of land cover in predicting SIF, compared to alternative environmental and meteorological data, and model predictions were thus not based on land cover ([58]). Our understanding is that this inability to correlate the two data products might be partly caused by uncertainties in both land cover ([59]) and SIF data, as well as by the resolution mismatch.

4.3. Elevation

SIF values were shown to be strictly connected to elevation gradients at the available spatial resolution. Chen et al. (2019, [57]) found significant altitude dependency in inter-annual GPP variations related to phenological and physiological variations, especially at high elevations, which is in line with our findings on land phenology metrics.

In regard to data quality, missing data and an overall inability to accurately characterize the higher altitudes might cause biases in carbon flux estimation from e.g. alpine grassland ecosystems, which are only present above the treeline but still account for an appreciable portion of the productivity of the Alps and of other high elevation regions (for instance, see [60]). It would be interesting to see whether this limitation could be resolved through the use of higher resolution data, or rather, if high elevation, cloud-covered, and often snow-covered habitats are per-se unaccountable for through remotely sensed fluorescence measurements, which would demand for alternative methods to be integrated in carbon-flux models in order to account for alpine grasslands or similarly (to satellite sensors) inaccessible habitats.

4.4. Phenology

The shift in DOY for each phenological indicator was not found to be constant: while SOS and POS generally tended to shift to earlier dates with lower elevation, with the potential exclusion of high- to mid-elevation adapted plant species such as conifers, EOS did not seem to vary considerably for most of the land cover classes analysed. This might be caused by specific ecological strategies of plant functional groups that are adapted to more extreme environments, in terms of temperature extremes, that might lead to freezing of and/or damage to photosynthetic plant tissues active at late DOY.

Evolutionary adaptations could have been developed by such plants as a form of risk aversion strategy, shutting down the photosynthetic machinery at a specific length of the day, independently of the altitude or temperature, resulting in abrupt EOS metrics; it is in fact known that carbon assimilation is often light-limited during autumn ([61]). Conversely, alternative causes of anticipated EOS might be related to environmental constraints such as photoperiod, temperature, soil moisture ([62], [63], [64], [65]), or a combination of all these factors. If we assume that lower elevation communities behave as higher elevation plants would when exposed to a warming climate scenario in the Alps, this implies that increases in temperature might only partially and asymmetrically affect the length of the growing season, effectively hindering an increase in carbon sequestration potential. In addition, carbon dynamics in autumn have been shown to be dominated by ecosystem respiration over photosynthesis, which can hinder the net carbon uptake even further ([66], [67]).

Overall, a shift in phenological timing generally resulting in longer growing season at lower elevations was found, which is in line with known altitudinal dynamics, and is thought to be comparable to trends that have emerged at the high latitudes due to increased temperatures ([65], [68], [69], [70], [71], [72]). We argue that the temperature increase expected at high latitudes might be confronted to the relationship between higher and lower elevations within the Alps.

4.5. SIF-GPP Relationship

Several studies have suggested that satellite-based SIF and modelled GPP are linearly linked but ecosystem-specific in various biomes ([8], [18], [19], [20], [21], [73]), while not necessarily linear when considering short or instantaneous timescales ([17]), since temporal averaging is known to tend towards linearization ([74], [75]). Other studies have outlined how a universal relationship might indeed exist ([76], [22]), however, differences in physiology and phenology between plant species or functional types, as well as complex canopy structures within different habitats, may prevent the development of such a universal relationship ([16], [77]). We found that a linear model was able to describe the link between SIF and GPP at most of the sites investigated, but the explained variability was sometimes low (R^2 as low as 0.30 and 0.29 at tower sites CH-Dav and CH-Oe2, respectively, see Table 5), and the relationship seemed mostly biome-specific. Another study on the Tibetan Plateau reported biome-specific SIF-GPP relationships ([57]), but differences between sites of the same land cover type were

still noticed, suggesting that site variability is likely to increase uncertainty even when comparing the slope at different sites of the same biome. Spatial variation within SIF pixels was reported to introduce additional uncertainty in the SIF-GPP relationship, which we argue to likely be linked to data resolution. In our study, low explained variability at specific sites is thought to be mostly connected to low data availability, or due to the mismatch in data resolution, since coarse spatial and temporal intervals are not able to capture the same trends and differences recorded by ground Eddy-Covariance flux towers.

In fact, the same resolution mismatch applies to ground-based GPP estimates, whose footprint from EC-flux towers is much smaller than most of the current SIF products. The Orbiting Carbon Observatory 2 (OCO-2) launched in July 2014 provides measurements at much finer resolution (1.3 km x 2.25 km), which have been shown to strongly correlate to tower-based GPP ([44], [76], [78], [79], [22], [80]), but its sparse spatial and temporal coverage hinders the evaluation and monitoring of SIF ([81]) outside of the target locations specific to the mission ([25]).

4.6. Outlook

A preliminary comparison with SIF data from the OCO-2 dataset was performed (results not shown), but a more in-depth analysis at appropriate locations would be needed in order to highlight the potential of finer-scale SIF data to monitor heterogeneous landscapes more efficiently. In particular, the nature of OCO-2 sparse spatial and temporal coverage, as well as the resolution mismatch with other satellite measurements and derived products – in our case, to the 0.05° spatial aggregation of the GOME-2 downscaled dataset – challenge the comparison to point-specific EC-flux tower GPP data as well as to continuous SIF measurements from other instruments.

The connection between SIF and cloud cover is interesting and could be investigated further: it remains unclear whether gaps in data availability within the Alps are to be associated with the heavy cloud cover, to a general lack of vegetation in certain regions at high elevations, or both. Snow cover might also be investigated, as it could explain some of the seasonal variability in SIF, especially at the beginning and at the end of the season, as shown by the work of Qiu et al. (2019, [82]) in the Tibetan Plateau. In particular, SIF might be confronted both to precipitation and snow cover data, which could help to explain patterns in missing data, seasonal and inter-annual variability,

phenology, and potentially even improve our understanding of SIF as a measure of water stress.

Several data-driven and machine learning approaches have recently been applied to develop continuous global SIF datasets, including the one used in this study ([1], [29], [31], [83], [58]), but all are generally provided at the 0.05° pixel. To address the current lack of suitable datasets for the Alps, similar methods could be applied on the basis of TROPOMI (which provides data with a $3.5 \times 7 \text{ km}^2$ resolution at nadir), TanSat (CarbonSat), OCO-2, or a combination of different datasets, with the aim of developing a SIF product with the fine resolution needed to analyse highly heterogeneous landscapes. ESA's FLuorescence EXplorer (FLEX, [84], [85], [86]) mission specifically designed for continuous SIF measurements, with 300 m x 300 m spatial resolution and due to launch in 2022, will substantially improve the quality of available SIF data. However, long running datasets will still be needed in order to evaluate long-term temporal trends in face of the fast advancing climate challenges we are confronted with today, and thus the development of reliable, fine scale downscaled products based on currently available SIF data should remain a focus of further research.

5. Conclusions

To the best of our knowledge, this is the first study that investigates SIF and the connection between SIF and GPP in the Greater Alpine Space. We found that current data resolution of downscaled SIF products can only be used to infer coarse scale spatial patterns and seasonal trends, whereas differences below the ecosystem scale and long-term trend analysis are hindered by the lack of precision and gaps in the dataset.

We found that the resolution mismatch between SIF and land cover data resulted in a likely underrepresentation of several biome types connected to human activities, including agricultural landscapes, and to many high elevation habitats typical of the Alps. Additionally, missing data at the high elevations hindered the analysis of plant productivity and phenology for ecosystems that include alpine pastures, grasslands and shrub communities. Land phenology metrics could still be inferred for most of the land cover classes, but the small sample size used for the fit of underrepresented habitat types is likely to affect the outcomes. Similarly, the resolution mismatch between footprint sizes of eddy covariance flux towers and the downscaled GOME-2 SIF product utilized limits the ability to validate the satellite-derived data and to evaluate the GPP-SIF relationships at the tower sites. We argue that in the Alps, SIF is strongly correlated to elevation and land cover, and that the relationship towards GPP might be biome-specific.

The advent of the planned FLEX mission will greatly improve our ability to use SIF for habitat monitoring and yearly stress detection, but long-running datasets at fine resolution might still be needed in order to analyse year-to-year variations and long-term trends in highly heterogeneous landscapes, which are also highly susceptible to climate change and thus should be focus of primary research interest for model implementation and mitigation strategies.

Further research is needed to mechanistically link sun-induced chlorophyll fluorescence to ecosystem productivity, stress detection, and ultimately to carbon sequestration potential, in order to improve our understanding of carbon dynamics and ecosystem response to climate change.

6. Literature

- [1] G. Duveiller *et al.*, 'A spatially downscaled sun-induced fluorescence global product for enhanced monitoring of vegetation productivity', *Earth Syst. Sci. Data Discuss.*, pp. 1–24, Aug. 2019, doi: 10.5194/essd-2019-121.
- [2] C. Beer *et al.*, 'Terrestrial Gross Carbon Dioxide Uptake: Global Distribution and Covariation with Climate', *Science*, vol. 329, no. 5993, pp. 834–838, Aug. 2010, doi: 10.1126/science.1184984.
- [3] M. Jung, M. Reichstein, and A. Bondeau, 'Towards global empirical upscaling of FLUXNET eddy covariance observations: validation of a model tree ensemble approach using a biosphere model', *Biogeosciences*, vol. 6, no. 10, pp. 2001–2013, Oct. 2009, doi: <https://doi.org/10.5194/bg-6-2001-2009>.
- [4] G. Tramontana *et al.*, 'Predicting carbon dioxide and energy fluxes across global 2 FLUXNET sites with regression algorithms', . CC, p. 34, 2016.
- [5] S. Z. Dobrowski, J. C. Pushnik, P. J. Zarco-Tejada, and S. L. Ustin, 'Simple reflectance indices track heat and water stress-induced changes in steady-state chlorophyll fluorescence at the canopy scale', *Remote Sens. Environ.*, vol. 97, no. 3, pp. 403–414, Aug. 2005, doi: 10.1016/j.rse.2005.05.006.
- [6] F. Daumard *et al.*, 'A Field Platform for Continuous Measurement of Canopy Fluorescence', *IEEE Trans. Geosci. Remote Sens.*, vol. 48, no. 9, pp. 3358–3368, Sep. 2010, doi: 10.1109/TGRS.2010.2046420.
- [7] P. J. Zarco-Tejada, A. Morales, L. Testi, and F. J. Villalobos, 'Spatio-temporal patterns of chlorophyll fluorescence and physiological and structural indices acquired from hyperspectral imagery as compared with carbon fluxes measured with eddy covariance', *Remote Sens. Environ.*, vol. 133, pp. 102–115, Jun. 2013, doi: 10.1016/j.rse.2013.02.003.
- [8] X. Yang *et al.*, 'Solar-induced chlorophyll fluorescence that correlates with canopy photosynthesis on diurnal and seasonal scales in a temperate deciduous forest', *Geophys. Res. Lett.*, vol. 42, no. 8, pp. 2977–2987, Apr. 2015, doi: 10.1002/2015GL063201.
- [9] K. Kramer *et al.*, 'Evaluation of six process-based forest growth models using eddy-covariance measurements of CO₂ and H₂O fluxes at six forest sites in Europe', *Glob. Change Biol.*, vol. 8, no. 3, pp. 213–230, Mar. 2002, doi: 10.1046/j.1365-2486.2002.00471.x.
- [10] S. Zaehle, S. Sitch, B. Smith, and F. Hatterman, 'Effects of parameter uncertainties on the modeling of terrestrial biosphere dynamics: PARAMETER-BASED UNCERTAINTY OF A DGVM', *Glob. Biogeochem. Cycles*, vol. 19, no. 3, Sep. 2005, doi: 10.1029/2004GB002395.
- [11] M. Jung *et al.*, 'Uncertainties of modeling gross primary productivity over Europe: A systematic study on the effects of using different drivers and terrestrial biosphere models: EFFECTS ON SIMULATED GPP', *Glob. Biogeochem. Cycles*, vol. 21, no. 4, p. n/a-n/a, Dec. 2007, doi: 10.1029/2006GB002915.
- [12] J. L. Monteith, 'Solar Radiation and Productivity in Tropical Ecosystems', *J. Appl. Ecol.*, vol. 9, no. 3, p. 747, Dec. 1972, doi: 10.2307/2401901.
- [13] C. Frankenberg *et al.*, 'New global observations of the terrestrial carbon cycle from GOSAT: Patterns of plant fluorescence with gross primary productivity', *Geophys. Res. Lett.*, vol. 38, no. 17, pp. 1–6, 2011, doi: 10.1029/2011GL048738.
- [14] J. Joiner, Y. Yoshida, A. P. Vasilkov, Y. Yoshida, L. A. Corp, and E. M. Middleton, 'First observations of global and seasonal terrestrial chlorophyll fluorescence from space', *Biogeosciences*, vol. 8, no. 3, pp. 637–651, 2011, doi: 10.5194/bg-8-637-2011.

- [15] J. Joiner *et al.*, 'Global monitoring of terrestrial chlorophyll fluorescence from moderate-spectral-resolution near-infrared satellite measurements: methodology, simulations, and application to GOME-2', *Atmospheric Meas. Tech.*, vol. 6, no. 10, pp. 2803–2823, 2013, doi: 10.5194/amt-6-2803-2013.
- [16] M. Jung *et al.*, 'Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations', *J. Geophys. Res. Biogeosciences*, vol. 116, no. G3, 2011, doi: 10.1029/2010JG001566.
- [17] A. Damm *et al.*, 'Far-red sun-induced chlorophyll fluorescence shows ecosystem-specific relationships to gross primary production: An assessment based on observational and modeling approaches', *Remote Sens. Environ.*, vol. 166, pp. 91–105, 2015, doi: 10.1016/j.rse.2015.06.004.
- [18] L. Guanter *et al.*, 'Retrieval and global assessment of terrestrial chlorophyll fluorescence from GOSAT space measurements', *Remote Sens. Environ.*, vol. 121, pp. 236–251, 2012, doi: 10.1016/j.rse.2012.02.006.
- [19] L. Guanter *et al.*, 'Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence', *Proc. Natl. Acad. Sci.*, vol. 111, no. 14, pp. E1327–E1333, 2014, doi: 10.1073/pnas.1320008111.
- [20] N. C. Parazoo *et al.*, 'Terrestrial gross primary production inferred from satellite fluorescence and vegetation models', *Glob. Change Biol.*, vol. 20, no. 10, pp. 3103–3121, 2014, doi: 10.1111/gcb.12652.
- [21] A. F. J. Sanders, W. W. Verstraeten, M. L. Kooreman, T. C. Van Leth, J. Beringer, and J. Joiner, 'Spaceborne Sun-Induced Vegetation Fluorescence Time Series from 2007 to 2015 Evaluated with Australian Flux Tower Measurements', *Remote Sens.*, vol. 8, no. 11, p. 895, Nov. 2016, doi: 10.3390/rs8110895.
- [22] Y. Sun *et al.*, 'OCO-2 advances photosynthesis observation from space via solar-induced chlorophyll fluorescence.', *Science*, vol. 358, no. 6360, p. eaam5747, Oct. 2017, doi: 10.1126/science.aam5747.
- [23] J.-E. Lee *et al.*, 'Forest productivity and water stress in Amazonia: observations from GOSAT chlorophyll fluorescence', *Proc. R. Soc. B Biol. Sci.*, vol. 280, no. 1761, p. 20130171, Jun. 2013, doi: 10.1098/rspb.2013.0171.
- [24] T. S. Magney *et al.*, 'Mechanistic evidence for tracking the seasonality of photosynthesis with solar-induced fluorescence', *Proc. Natl. Acad. Sci.*, vol. 116, no. 24, pp. 11640–11645, Jun. 2019, doi: 10.1073/pnas.1900278116.
- [25] N. C. Parazoo *et al.*, 'Towards a Harmonized Long-Term Spaceborne Record of Far-Red Solar-Induced Fluorescence', *J. Geophys. Res. Biogeosciences*, pp. 2518–2539, 2019, doi: 10.1029/2019jg005289.
- [26] J. Fischer, W. Cordes, A. Schmitz-Peiffer, W. Renger, and P. Mörl, 'Detection of Cloud-Top Height from Backscattered Radiances within the Oxygen A Band. Part 2: Measurements', *J. Appl. Meteorol.*, vol. 30, no. 9, pp. 1260–1267, Sep. 1991, doi: 10.1175/1520-0450(1991)030<1260:DOCTHF>2.0.CO;2.
- [27] D. Crisp *et al.*, 'The Orbiting Carbon Observatory (OCO) mission', *Adv. Space Res.*, vol. 34, no. 4, pp. 700–709, Jan. 2004, doi: 10.1016/j.asr.2003.08.062.
- [28] G. Duveiller and A. Cescatti, 'Spatially downscaling sun-induced chlorophyll fluorescence leads to an improved temporal correlation with gross primary productivity', *Remote Sens. Environ.*, vol. 182, pp. 72–89, 2016, doi: 10.1016/j.rse.2016.04.027.
- [29] M. Chen, N. Zeng, G. Asrar, and Y. Liu, 'Using model-data fusion to downscale solar-induced fluorescence data into a higher spatiotemporal resolution', in *Land Surface and Cryosphere Remote Sensing IV*, 2018, p. 30, doi: 10.1117/12.2324582.

- [30] X. Liu *et al.*, 'Downscaling of solar-induced chlorophyll fluorescence from canopy level to photosystem level using a random forest model', *Remote Sens. Environ.*, Jun. 2018, doi: 10.1016/j.rse.2018.05.035.
- [31] L. Yu, J. Wen, C. Y. Chang, C. Frankenberg, and Y. Sun, 'High Resolution Global Contiguous Solar-Induced Chlorophyll Fluorescence (SIF) of Orbiting Carbon Observatory-2 (OCO-2)', *Geophys. Res. Lett.*, vol. 2, no. December, 2018, doi: 10.1029/2018gl081109.
- [32] Z. Zhang, Y. Zhang, J. Joiner, and M. Migliavacca, 'Angle matters: Bidirectional effects impact the slope of relationship between gross primary productivity and sun-induced chlorophyll fluorescence from Orbiting Carbon Observatory-2 across biomes', *Glob. Change Biol.*, vol. 24, no. 11, pp. 5017–5020, Nov. 2018, doi: 10.1111/gcb.14427.
- [33] X. Li and J. Xiao, 'Mapping photosynthesis solely from solar-induced chlorophyll fluorescence: A global, fine-resolution dataset of gross primary production derived from OCO-2', *Remote Sens.*, vol. 11, no. 21, p. 2563, Oct. 2019, doi: 10.3390/rs11212563.
- [34] R. B. Myneni, C. D. Keeling, C. J. Tucker, G. Asrar, and R. R. Nemani, 'Increased plant growth in the northern high latitudes from 1981 to 1991', *Nature*, vol. 386, no. 6626, pp. 698–702, Apr. 1997, doi: 10.1038/386698a0.
- [35] J. T. Randerson, C. B. Field, I. Y. Fung, and P. P. Tans, 'Increases in early season ecosystem uptake explain recent changes in the seasonal cycle of atmospheric CO₂ at high northern latitudes', *Geophys. Res. Lett.*, vol. 26, no. 17, pp. 2765–2768, 1999, doi: 10.1029/1999GL900500.
- [36] M. Forkel *et al.*, 'Enhanced seasonal CO₂ exchange caused by amplified plant productivity in northern ecosystems', *Science*, vol. 351, no. 6274, pp. 696–699, Feb. 2016, doi: 10.1126/science.aac4971.
- [37] M. W. Trahan and B. A. Schubert, 'Temperature-induced water stress in high-latitude forests in response to natural and anthropogenic warming', *Glob. Change Biol.*, vol. 22, no. 2, pp. 782–791, 2016, doi: 10.1111/gcb.13121.
- [38] J.-P. Theurillat and A. Guisan, 'Potential Impact of Climate Change on Vegetation in the European Alps: A Review', *Clim. Change*, vol. 50, no. 1–2, pp. 77–109, Jul. 2001, doi: 10.1023/A:1010632015572.
- [39] M. Beniston, 'Climatic Change in Mountain Regions: A Review of Possible Impacts', in *Climate Variability and Change in High Elevation Regions: Past, Present & Future*, vol. 15, H. F. Diaz, Ed. Dordrecht: Springer Netherlands, 2003, pp. 5–31.
- [40] A. Becker, C. Körner, J.-J. Brun, A. Guisan, and U. Tappeiner, 'Ecological and Land Use Studies Along Elevational Gradients', *Mt. Res. Dev.*, vol. 27, no. 1, pp. 58–65, Feb. 2007, doi: 10.1659/0276-4741(2007)27[58:EALUSA]2.0.CO;2.
- [41] A. Gobiet, S. Kotlarski, M. Beniston, G. Heinrich, J. Rajczak, and M. Stoffel, '21st century climate change in the European Alps—A review', *Sci. Total Environ.*, vol. 493, pp. 1138–1151, Sep. 2014, doi: 10.1016/j.scitotenv.2013.07.050.
- [42] M. Rogora *et al.*, 'Assessment of climate change effects on mountain ecosystems through a cross-site analysis in the Alps and Apennines', *Sci. Total Environ.*, vol. 624, pp. 1429–1442, May 2018, doi: 10.1016/j.scitotenv.2017.12.155.
- [43] L. M. Zuromski *et al.*, 'Solar-Induced Fluorescence Detects Interannual Variation in Gross Primary Production of Coniferous Forests in the Western United States', *Geophys. Res. Lett.*, vol. 45, no. 14, pp. 7184–7193, 2018, doi: 10.1029/2018GL077906.
- [44] X. Li, J. Xiao, and B. He, 'Chlorophyll fluorescence observed by OCO-2 is strongly related to gross primary productivity estimated from flux towers in temperate forests', *Remote Sens. Environ.*, vol. 204, no. September 2017, pp. 659–671, 2018, doi: 10.1016/j.rse.2017.09.034.

- [45] A. Gonsamo, J. M. Chen, and P. D'Odorico, 'Deriving land surface phenology indicators from CO₂ eddy covariance measurements', *Ecol. Indic.*, vol. 29, pp. 203–207, 2013, doi: 10.1016/j.ecolind.2012.12.026.
- [46] J. Cohen and P. Cohen, 'Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences', p. 18.
- [47] C. Körner, *Alpine Plant Life: Functional Plant Ecology of High Mountain Ecosystems ; with 47 Tables*. Springer Science & Business Media, 2003.
- [48] Q. Chang *et al.*, 'Assessing consistency of spring phenology of snow-covered forests as estimated by vegetation indices, gross primary production, and solar-induced chlorophyll fluorescence', *Agric. For. Meteorol.*, vol. 275, pp. 305–316, Sep. 2019, doi: 10.1016/J.AGRFORMET.2019.06.002.
- [49] C. Q. Tang and M. Ohsawa, 'Zonal transition of evergreen, deciduous, and coniferous forests along the altitudinal gradient on a humid subtropical mountain, Mt. Emei, Sichuan, China', *Plant Ecol.*, vol. 133, no. 1, pp. 63–78, 1997, doi: 10.1023/A:1009729027521.
- [50] J. Gellhorn, 'The Biology of Alpine Habitats, by Laszlo Nagy and Georg Grabherr', *Arct. Antarct. Alp. Res.*, vol. 42, no. 1, pp. 130–130, Feb. 2010, doi: 10.1657/1938-4246-42.1.130a.
- [51] C. Emmel *et al.*, 'Integrated management of a Swiss cropland is not sufficient to preserve its soil carbon pool in the long term', *Biogeosciences*, vol. 15, no. 17, pp. 5377–5393, Sep. 2018, doi: <https://doi.org/10.5194/bg-15-5377-2018>.
- [52] G. Öquist and N. P. A. Huner, 'Photosynthesis of overwintering evergreen plants', *Annu. Rev. Plant Biol.*, vol. 54, no. 1, pp. 329–355, Jun. 2003, doi: 10.1146/annurev.arplant.54.072402.115741.
- [53] J. B. Nippert, R. A. Duursma, and J. D. Marshall, 'Seasonal variation in photosynthetic capacity of montane conifers', *Funct. Ecol.*, vol. 18, no. 6, pp. 876–886, 2004, doi: 10.1111/j.0269-8463.2004.00909.x.
- [54] W. W. Adams, C. R. Zarter, V. Ebbert, and B. Demmig-Adams, 'Photoprotective Strategies of Overwintering Evergreens', *BioScience*, vol. 54, no. 1, pp. 41–49, Jan. 2004, doi: 10.1641/0006-3568(2004)054[0041:PSOOE]2.0.CO;2.
- [55] P. Jahns and A. R. Holzwarth, 'The role of the xanthophyll cycle and of lutein in photoprotection of photosystem II', *Biochim. Biophys. Acta BBA - Bioenerg.*, vol. 1817, no. 1, pp. 182–193, Jan. 2012, doi: 10.1016/j.bbabi.2011.04.012.
- [56] A. Verhoeven, 'Sustained energy dissipation in winter evergreens', *New Phytol.*, vol. 201, no. 1, pp. 57–65, 2014, doi: 10.1111/nph.12466.
- [57] S. Chen, Y. Huang, S. Gao, and G. Wang, 'Impact of physiological and phenological change on carbon uptake on the Tibetan Plateau revealed through GPP estimation based on spaceborne solar-induced fluorescence', *Sci. Total Environ.*, vol. 663, pp. 45–59, May 2019, doi: 10.1016/j.scitotenv.2019.01.324.
- [58] X. Li and J. Xiao, 'A Global, 0.05-Degree Product of Solar-Induced Chlorophyll Fluorescence Derived from OCO-2, MODIS, and Reanalysis Data', *Remote Sens.*, vol. 11, no. 5, pp. 517–541, Mar. 2019, doi: 10.3390/rs11050517.
- [59] R. G. Congalton, J. Gu, K. Yadav, P. Thenkabail, and M. Ozdogan, 'Global Land Cover Mapping: A Review and Uncertainty Analysis', *Remote Sens.*, vol. 6, no. 12, pp. 12070–12093, Dec. 2014, doi: 10.3390/rs61212070.
- [60] H. Chen *et al.*, 'The impacts of climate change and human activities on biogeochemical cycles on the Qinghai-Tibetan Plateau', *Glob. Change Biol.*, vol. 19, no. 10, pp. 2940–2955, 2013, doi: 10.1111/gcb.12277.
- [61] T. Suni, F. Berninger, T. Markkanen, P. Keronen, Ü. Rannik, and T. Vesala, 'Interannual variability and timing of growing-season CO₂ exchange in a boreal forest', *J. Geophys. Res. Atmospheres*, vol. 108, no. D9, 2003, doi: 10.1029/2002JD002381.

- [62] T. T. Kozłowski and S. G. Pallardy, *Physiology of Woody Plants*. Elsevier, 1996.
- [63] Y. Vitasse, A. J. Porté, A. Kremer, R. Michalet, and S. Delzon, 'Responses of canopy duration to temperature changes in four temperate tree species: relative contributions of spring and autumn leaf phenology', *Oecologia*, vol. 161, no. 1, pp. 187–198, Aug. 2009, doi: 10.1007/s00442-009-1363-4.
- [64] D. Dragoni and A. F. Rahman, 'Trends in fall phenology across the deciduous forests of the Eastern USA', *Agric. For. Meteorol.*, vol. 157, pp. 96–105, May 2012, doi: 10.1016/j.agrformet.2012.01.019.
- [65] J. Barichivich *et al.*, 'Large-scale variations in the vegetation growing season and annual cycle of atmospheric CO₂ at high northern latitudes from 1950 to 2011', *Glob. Change Biol.*, vol. 19, no. 10, pp. 3167–3183, 2013, doi: 10.1111/gcb.12283.
- [66] S. Piao *et al.*, 'Net carbon dioxide losses of northern ecosystems in response to autumn warming', *Nature*, vol. 451, no. 7174, pp. 49–52, Jan. 2008, doi: 10.1038/nature06444.
- [67] J. Barichivich, K. R. Briffa, T. J. Osborn, T. M. Melvin, and J. Caesar, 'Thermal growing season and timing of biospheric carbon uptake across the Northern Hemisphere', *Glob. Biogeochem. Cycles*, vol. 26, no. 4, 2012, doi: 10.1029/2012GB004312.
- [68] E. E. Cleland, I. Chuine, A. Menzel, H. A. Mooney, and M. D. Schwartz, 'Shifting plant phenology in response to global change', *Trends Ecol. Evol.*, vol. 22, no. 7, pp. 357–365, Jul. 2007, doi: 10.1016/j.tree.2007.04.003.
- [69] I. Garonna, R. de Jong, A. J. W. de Wit, C. A. Mücher, B. Schmid, and M. E. Schaepman, 'Strong contribution of autumn phenology to changes in satellite-derived growing season length estimates across Europe (1982–2011)', *Glob. Change Biol.*, vol. 20, no. 11, pp. 3457–3470, 2014, doi: 10.1111/gcb.12625.
- [70] A. Gonsamo and J. M. Chen, 'Circumpolar vegetation dynamics product for global change study', *Remote Sens. Environ.*, vol. 182, pp. 13–26, Sep. 2016, doi: 10.1016/j.rse.2016.04.022.
- [71] A. Menzel *et al.*, 'European phenological response to climate change matches the warming pattern', *Glob. Change Biol.*, vol. 12, no. 10, pp. 1969–1976, 2006, doi: 10.1111/j.1365-2486.2006.01193.x.
- [72] A. Gonsamo, J. M. Chen, and Y. W. Ooi, 'Peak season plant activity shift towards spring is reflected by increasing carbon uptake by extratropical ecosystems', *Glob. Change Biol.*, vol. 24, no. 5, pp. 2117–2128, 2018, doi: 10.1111/gcb.14001.
- [73] A. Porcar-Castell *et al.*, 'Linking chlorophyll a fluorescence to photosynthesis for remote sensing applications: Mechanisms and challenges', *J. Exp. Bot.*, vol. 65, no. 15, pp. 4065–4095, 2014, doi: 10.1093/jxb/eru191.
- [74] A. Ruimy, P. G. Jarvis, D. D. Baldocchi, and B. Saugier, 'CO₂ Fluxes over Plant Canopies and Solar Radiation: A Review', in *Advances in Ecological Research*, vol. 26, M. Begon and A. H. Fitter, Eds. Academic Press, 1995, pp. 1–68.
- [75] Y. Zhang *et al.*, 'Model-based analysis of the relationship between sun-induced chlorophyll fluorescence and gross primary production for remote sensing applications', *Remote Sens. Environ.*, vol. 187, pp. 145–155, Dec. 2016, doi: 10.1016/j.rse.2016.10.016.
- [76] X. Li *et al.*, 'Solar-induced chlorophyll fluorescence is strongly correlated with terrestrial photosynthesis for a wide variety of biomes: First global analysis based on OCO-2 and flux tower observations', *Glob. Change Biol.*, vol. 24, no. 9, pp. 3990–4008, Sep. 2018, doi: 10.1111/gcb.14297.
- [77] J. Gamon, 'Reviews and Syntheses: optical sampling of the flux tower footprint', *Pap. Nat. Resour.*, Jan. 2015.
- [78] M. Verma *et al.*, 'Effect of environmental conditions on the relationship between solar-induced fluorescence and gross primary productivity at an OzFlux grassland site', *J.*

- Geophys. Res. Biogeosciences*, vol. 122, no. 3, pp. 716–733, Mar. 2017, doi: 10.1002/2016JG003580.
- [79] J. D. Wood, T. J. Griffis, J. M. Baker, C. Frankenberg, M. Verma, and K. Yuen, ‘Multiscale analyses of solar-induced fluorescence and gross primary production’, *Geophys. Res. Lett.*, vol. 44, no. 1, pp. 533–541, 2017, doi: 10.1002/2016GL070775.
- [80] Y. Sun *et al.*, ‘Overview of Solar-Induced chlorophyll Fluorescence (SIF) from the Orbiting Carbon Observatory-2: Retrieval, cross-mission comparison, and global monitoring for GPP’, *Remote Sens. Environ.*, vol. 209, pp. 808–823, May 2018, doi: 10.1016/j.rse.2018.02.016.
- [81] X. Lu, X. Cheng, X. Li, and J. Tang, ‘Opportunities and challenges of applications of satellite-derived sun-induced fluorescence at relatively high spatial resolution’, *Sci. Total Environ.*, vol. 619–620, pp. 649–653, 2018, doi: 10.1016/j.scitotenv.2017.11.158.
- [82] B. Qiu *et al.*, ‘Satellite-observed solar-induced chlorophyll fluorescence reveals higher sensitivity of alpine ecosystems to snow cover on the Tibetan Plateau’, *Agric. For. Meteorol.*, vol. 271, pp. 126–134, Jun. 2019, doi: 10.1016/j.agrformet.2019.02.045.
- [83] Y. Zhang, J. Joiner, S. H. Alemohammad, S. Zhou, and P. Gentile, ‘A global spatially contiguous solar-induced fluorescence (CSIF) dataset using neural networks’, *Biogeosciences*, vol. 15, no. 19, pp. 5779–5800, Oct. 2018, doi: 10.5194/bg-15-5779-2018.
- [84] J. F. Moreno *et al.*, ‘Fluorescence explorer (FLEX): An optimised payload to map vegetation photosynthesis from space’, in *AIAA 57th International Astronautical Congress, IAC 2006*, 2006, vol. 3, pp. 2065–2074.
- [85] *Report for Mission selection: carbonsat flex*. Noordwijk, the Netherlands: ESA Communications, 2015.
- [86] M. Drusch *et al.*, ‘The FLUorescence EXplorer Mission Concept-ESA’s Earth Explorer 8’, *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 3, pp. 1273–1284, 2017, doi: 10.1109/TGRS.2016.2621820.

Supplementary Material

Table 7 – Statistics for the SIF-LCC Quantiles.

SIF mean values vs fraction means of land cover classes over quantiles for specific cumulative probabilities.

Land Cover Class (LCC)	Cum_Prob	SIF_mean	SIF_std	LCC_mean	LCC_std
Artificial	0.50	0.63	0.33	0.11	0.09
TempCrops	0.50	0.63	0.33	0.25	0.18
PermCrops	0.50	0.60	0.33	0.17	0.14
Pastures	0.50	0.64	0.32	0.20	0.13
MixedCrops	0.50	0.62	0.34	0.19	0.11
Broadleaves	0.50	0.62	0.36	0.36	0.20
Conifers	0.50	0.56	0.28	0.46	0.16
MixedForests	0.50	0.62	0.33	0.30	0.14
Grasslands	0.50	0.52	0.28	0.38	0.15
Glaciers	0.50	0.45	0.24	0.45	0.25
Water	0.50	0.56	0.32	0.13	0.16
Artificial	0.75	0.63	0.33	0.16	0.10
TempCrops	0.75	0.64	0.34	0.38	0.18
PermCrops	0.75	0.61	0.32	0.27	0.14
Pastures	0.75	0.68	0.33	0.29	0.13
MixedCrops	0.75	0.63	0.35	0.27	0.11
Broadleaves	0.75	0.65	0.37	0.51	0.16
Conifers	0.75	0.55	0.27	0.59	0.12
MixedForests	0.75	0.62	0.33	0.41	0.11
Grasslands	0.75	0.52	0.27	0.49	0.12
Glaciers	0.75	0.36	0.20	0.66	0.18
Water	0.75	0.51	0.31	0.22	0.18
Artificial	0.90	0.62	0.33	0.24	0.10
TempCrops	0.90	0.66	0.34	0.56	0.14
PermCrops	0.90	0.61	0.32	0.41	0.11
Pastures	0.90	0.74	0.34	0.42	0.11
MixedCrops	0.90	0.66	0.35	0.37	0.10
Broadleaves	0.90	0.66	0.39	0.68	0.10
Conifers	0.90	0.53	0.25	0.71	0.08
MixedForests	0.90	0.62	0.33	0.52	0.09
Grasslands	0.90	0.53	0.28	0.61	0.09
Glaciers	0.90	0.26	0.15	0.85	0.09
Water	0.90	0.44	0.28	0.39	0.18
Artificial	0.95	0.61	0.32	0.31	0.11
TempCrops	0.95	0.70	0.35	0.68	0.10
PermCrops	0.95	0.61	0.32	0.50	0.09
Pastures	0.95	0.77	0.34	0.50	0.10

*Satellite-based Sun-Induced Chlorophyll Fluorescence in the Greater Alpine Space:
Spatial Patterns and Relationship to Gross Primary Productivity*

MixedCrops	0.95	0.67	0.35	0.44	0.10
Broadleaves	0.95	0.67	0.41	0.76	0.07
Conifers	0.95	0.52	0.25	0.77	0.06
MixedForests	0.95	0.61	0.33	0.59	0.07
Grasslands	0.95	0.54	0.28	0.68	0.08
Glaciers	0.95	0.20	0.12	0.93	0.05
Water	0.95	0.35	0.24	0.53	0.16
Artificial	0.99	0.56	0.30	0.49	0.11
TempCrops	0.99	0.73	0.36	0.81	0.06
PermCrops	0.99	0.61	0.34	0.65	0.07
Pastures	0.99	0.84	0.36	0.67	0.06
MixedCrops	0.99	0.68	0.34	0.60	0.09
Broadleaves	0.99	0.67	0.42	0.88	0.04
Conifers	0.99	0.49	0.23	0.87	0.03
MixedForests	0.99	0.60	0.32	0.71	0.05
Grasslands	0.99	0.57	0.30	0.81	0.04
Glaciers	0.99	0.09	0.07	1.00	0.00
Water	0.99	0.20	0.15	0.77	0.07