**Are surface temperature and chlorophyll in a large deep lake
related? An analysis based on satellite observations in synergy with
hydrodynamic modelling and in-situ data**

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19 **Abstract.** Phytoplankton growth depends on various factors, and primarily on nutrient
20 availability, light and water temperature, whose distributions are largely controlled by
21 hydrodynamics. Our main objective is to analyse the link between spatial and temporal
22 variability of surface water temperature and algal concentration in a large lake by means of
23 remote sensing and hydrodynamic modelling. We compare ten years of satellite images showing
24 chlorophyll concentrations and surface water temperature of Lake Geneva. Our observations
25 suggest different correlations depending on the season. Elevated chlorophyll concentrations in
26 spring are correlated with warmer zones. But, in summer, higher chlorophyll concentrations are
27 observed in colder zones. We show with a three-dimensional hydrodynamic model that the
28 spatial variability of the surface water temperature reflects the upwelling and downwelling zones
29 resulting from wind forcing. In springtime, nearshore downwellings induce locally increased
30 surface temperature and stratification, which are associated with high chlorophyll concentration.
31 In summertime, colder surface temperature area, often interpreted as transient upwellings,
32 represents the thermal surface signature of wind-induced basin-scale internal waves, bringing
33 either nutrients or phytoplankton from deeper layers to the surface. Our study suggests the latter
34 to be the dominant process, with the basin-scale internal wave activity and associated transient
35 summertime upwellings and downwellings having little net effects on the algal concentration.
36 This study finally demonstrates the necessity to connect remote sensing retrievals and three-
37 dimensional hydrodynamic modelling to properly understand the dynamic of the lake
38 ecosystems.

39 **1 Introduction**

40 Photosynthetic growth of phytoplankton in surface waters depends mainly on light, temperature,
41 and nutrients (Reynolds, 2006). The seasonal and inter-annual variability of phytoplankton
42 dynamics is the result of complex interactions of temporally variable abiotic and biotic
43 parameters and mechanisms (Behrenfeld and Boss, 2014; Sommer et al., 2012) also depending
44 on other processes, such as competition or grazing. In temperate regions, seasonal stratification
45 governs these processes to a large extent, by limiting the upward flux of hypolimnetic nutrients
46 to the photic surface layer of lakes (epilimnion), where light is usually abundant in oligo- to
47 mesotrophic lakes (Sharples et al., 2001; Watanabe et al., 2016). During the stratified seasons,
48 nutrients are consumed in the photic surface layer (Sommer et al., 2012), and only limited
49 phytoplankton growth occurs after the first spring bloom, while phytoplankton growth
50 progressively moves to deeper layers (Barbiero and Tuchman, 2004; Dokulil and Teubner,
51 2012).

52 In spring, the increasing lake temperature governs phytoplankton growth by two
53 mechanisms: (i) acceleration of the physiological processes, such as nutrient uptake, growth and
54 respiration (Berger et al., 2010; Goldman and Carpenter, 1974), and (ii) development of the
55 thermal stratification of the water column (Diehl et al., 2002; Berger et al., 2010).

56 In summer, phytoplankton growth is often nutrient-limited. Long lasting coastal
57 upwelling has been identified as an important source of nutrients, when transported from the
58 deep water to the upper photic layer (Mackas et al., 1985). As a result, most of the primary
59 production in the global ocean takes place in upwelling regions (Falkowski et al., 1998; Gruber
60 et al., 2011). In lakes, with the exception of very large ones like Lake Baikal (Troitskaya et al.,
61 2015), upwelling of cold and nutrient-rich deep water are mostly wind-induced and are therefore

transient (Steissberg et al., 2005). MacIntyre and Jellison (2001) observed in a medium-sized lake (where Coriolis forces remain negligible) that strong wind-induced upwelling can increase nutrient upward flux and favour phytoplankton growth. Yet, the inverse effect was also observed. After a major storm event, cold hypolimnetic water in Lake Constance was correlated with significantly lower chlorophyll-*a* concentrations (CHL) than the warm, epilimnetic water (Rinke et al., 2009).

All the above-mentioned processes are associated with lateral variability in the dynamical behaviour of phytoplankton growth. Yet, lake monitoring strategies typically focus on sampling ecological parameters at the lake centre or at the deepest point, thereby neglecting spatial variability and littoral processes (Pomati et al., 2011). Traditional attempts to capture the lateral variability in phytoplankton horizontal dynamics require extensive *in-situ* measurements (Thackeray et al., 2004). Remote sensing applications for lake water composition (Giardino et al., 2001; Odermatt et al., 2012a) and lake surface water temperature (LSWT; (Oesch et al., 2005) have opened new perspectives for monitoring spatial and temporal water quality dynamics. However, satellite measurements remain limited in depth, i.e. to the first micrometers for LSWT and to roughly Secchi depth for the least attenuated wavelengths of reflected solar irradiation. The depth limited information and their temporal stochasticity call for an integration of both *in-situ* and remote sensing data into numerical models to constrain lake system studies. While this approach has often been applied in oceanography, examples of integration of *in-situ*, remote sensing and model data remain scarce in inland waters (Curtarelli et al., 2015; Wynne et al., 2013). This study examines the inter-seasonal relationships between satellite-observed LSWT and CHL in Lake Geneva. Data from the Advanced Very High Resolution Radiometer (AVHRR) on the US National Oceanic and Atmospheric Administration (NOAA) satellites are

85 used for LSWT, which is a relative indicator for physical phenomena, such as stratification and
 86 upwelling. CHL is derived from the MEdium Resolution Imaging Spectrometer (MERIS) full
 87 resolution images on the European Space Agency Environmental Satellite (ENVISAT). The
 88 investigations make use of all available data pairs (e.g. AVHRR and MERIS data) acquired
 89 during the ten years of ENVISAT operations (17th May 2002 to 8th April 2012).

91 **Figure 1.** Differences of chlorophyll (CHL) and lake surface water temperature (LSWT) relative
 92 to their spatial averages for two same-day scenes, one in spring (right) and one in autumn (left)
 93 2011. Both show spatial correlation between CHL and LSWT.

94 Based on intriguingly correlated remotely sensed CHL and LSWT image pairs (Figure 1),
 95 we formulate two season specific hypotheses on physical and biological in Lake Geneva. First, in
 96 spring, we expect a positive relationship between phytoplankton growth and temperature; or,
 97 implicitly, dependent on the stability of the water column. We expect that phytoplankton growth
 98 is enhanced in downwelling zones, where warm surface water is converging. Second, in summer
 99 and fall, and after the build-up of the seasonal thermocline and algae growth-induced surface

nutrient depletion, phytoplankton growth becomes nutrient-limited. We expect that phytoplankton growth is enhanced in upwelling zones.

These hypotheses are investigated using a spatial autocorrelation indicator (Moran's I) for satellite data pairs. Results are analysed with respect to *in-situ* data such as depth-dependent annual phosphorus and CHL concentrations and the short-term spatio-temporal change in the thermal structure as inferred from a three-dimensional (3D) hydrodynamic model.

2 Study area and data

2.1 Lake Geneva study site

Figure 2. Map of Lake Geneva with locations SHL2 (pink), Buchillon (green) and Pully (yellow). *In-situ* CHL calibration samples are regularly taken at SHL2. Temperatures measured at Buchillon and at SHL2 have been used for calibrating the three-dimensional Delft3D-Flow model. 20 m isolines are shown.

Lake Geneva (Figure 2) is a perialpine lake situated at an altitude of 372 m above sea level with a surface area, a total volume and a maximum depth of 580 km², 89 km³ and 309 m,

respectively. Its two main basins, the Grand Lac (“large lake”) and the Petit Lac (“small lake”) differ in average depth and volume (172 m and 96% vs. 41 m and 4 %). Lake Geneva is a warm monomictic lake with seasonal convective mixing reaching deepest typically in late February or early March. Depending on temperatures and wind intensities during winter, deep convective mixing usually does not extend over the entire water column (Rimet et al., 2009; Schwefel et al., 2016). Between 2002 and 2012, complete mixing took place only in March 2005, 2006 and 2012, redistributing nutrients and oxygen over the entire water column.

Figure 3. Concentrations of CHL during the productive season (March to October) in Lake Geneva. The data shown is based on bi-monthly in-situ measurements at SHL2 (Figure 2) for the period 2002-2012. Boxplot with whiskers length $1.5 (\pm 2.7 \sigma)$; outliers are not shown.

Phytoplankton peaks between one and three times per year (Kiefer et al., 2015), with the strongest blooms in spring. Spring CHL maxima are located near the surface, while later in the season they are found deeper (Figure 3). Phosphorus concentrations are typically high at the beginning of the productive season (Figure 4), currently at $\sim 18 \text{ mg m}^{-3}$, following the winter deep mixing of the water column. However, once the biological activity has started in spring, these nutrients are depleted in the photic surface layer (Figure 4). Spring time lake warming and subsequent onset of stratification cut off the light-abundant surface layer from the nutrient-rich

deeper layers. The nutrient depletion typically extends down to 35 – 50 m in Lake Geneva. Deeper layers maintain considerably higher average phosphate concentrations throughout the year (Figure 4).

Figure 4. a) Average annual cycle of phosphate concentrations at different depths (0-5 m, 35 m, 50 m, 100 m) for 2002 to 2010. Bold line: average per day of the year; shaded area: 95% confidence interval. b) Average annual cycle of LSWT, computed from horizontally-averaged AVHRR satellite images (2002-2012). Dashed line: average per day of the year; solid line: 10 days running mean.

2.2 Satellite data

2.2.1 Advanced Very High Resolution Radiometer data

Satellite images from the AVHRR sensor are routinely acquired by the Remote Sensing Research Group at the University of Bern (Riffler et al., 2015). The data is available from 1989 onwards at 1.1 km spatial resolution (at nadir) and temporal resolutions between one and ten images per 24 hours (Hüsler et al., 2011). In order to guarantee data homogeneity and continuity over the different AVHRR sensors of the NOAA and the European Meteorological Operational (MetOp) polar orbiting satellites, the data reprocessing comprehends radiometric time- and sensor-dependent calibration, precise geolocation, atmospheric correction, cloud masking and

151 time-series specific corrections (Oesch et al., 2005). Data from the satellites MetOp-A, NOAA
152 14 and NOAA 16 to 19 from 2002 to 2012 are used in this study. LSWT retrieval methods,
153 calibration, and validation are discussed in detail in Oesch et al. (2005) and Riffler et al. (2015).
154 Biases between AVHRR-derived LSWT and *in-situ* measurements are in the range of -0.5 to
155 +0.6 °C and root mean square errors are 1.0 to 1.6 °C (Riffler et al., 2015). The difference
156 between satellite-derived and *in-situ* measurements is mainly based on the fact, that a satellite
157 sensor retrieves only the signal from the upper most micrometre (skin temperature), whereas in-
158 situ devices are mounted in deeper layers (bulk temperature). A skin-to-bulk correction using
159 wind speed is applied to convert LSWT to *in-situ* and model bulk temperature. As shown by
160 Minnett et al. (2011), Wilson et al. (2013) and others, the bulk temperature can differ by up to
161 several K depending on meteorological conditions and water stratification. Therefore, skin-to-
162 bulk conversion is needed considering the different radiative processes between lake water and
163 atmosphere as well as mixing in the uppermost water layer. This correction reduces the bias to
164 ~0.2 °C (Riffler et al., 2015). Observations are averaged when more than one image per day is
165 available. Cloud masking is an essential step to guarantee the retrieval of surface temperature
166 unaffected by clouds or cloud shadows. Cloud detection is mainly based on CASPR (Cloud And
167 Surface Parameter Retrieval; Key, 2002) and cloud shadow is masked using the method of
168 Simpson and Stitt (1998). Due to the limited spectral resolution of the AVHRR sensor (only
169 three channels for VIS-NIR spectra and two channels for the thermal infrared) not all clouds
170 effects are detected. Consequently, a quality control procedure is applied to remove erroneous
171 pixels. This procedure includes spatial tests in a 3x3 surrounding, thresholds of reflectance
172 values, temperature margins etc. Detailed information is given in Riffler et al. (2015) and Hüsler
173 et al. (2011).

2.2.2 MEdium Resolution Imaging Spectrometer data

For the retrieval of CHL we use data acquired by the European Space Agency's (ESA) Medium Resolution Imaging Spectrometer (MERIS) between June 2002 and April 2012. In its default band configuration, MERIS measured radiance in 15 narrow spectral bands between 413 and 900 nm. The MERIS L1B data was processed using the ESA Calvalus portal (Fomferra et al., 2012) and dedicated methods for improved georectification (Bourg and Etanchaud, 2007), smile effect correction (Bouvet and Ramoino, 2010), valid water pixel identification (Idepix, Ruecas et al. (2014)) and CHL retrieval (FUB neural network; Schroeder et al. (2007)). The resulting CHL maps were collocated in a regularly-spaced grid of 270 m cell size, and calibrated and validated using 46 *in-situ* monitoring samples collected in Lake Geneva (Section 2.3.2) when a MERIS image was acquired on the same day (Kiefer et al., 2015). Concentrations for the top 5 m of the water column are averaged as reference for comparison with 3x3 pixel averaged CHL from MERIS.

The FUB algorithm performs water quality parameter retrieval using neural networks that were trained with radiative transfer simulations for bio-optical scattering and absorption properties in optically complex waters. The range of these simulations is up to 50 mg m⁻³ CHL, 50 g m⁻³ TSM and 1 m⁻¹ CDOM and thus suitable for Lake Geneva. Such retrieval algorithms make use of the quantitative relationship between phytoplankton pigment absorption and CHL, which is subject to relatively large uncertainty (Odermatt et al., 2012b). Therefore, we recalibrated the CHL levels provided by the FUB algorithm with the gain and offset of a zero intercept forced linear regression ($R^2 = 0.62$; Kiefer et al., 2015). The RMSE after calibration is 2.3 mg m⁻³, which means that for Lake Geneva, the performance of the whole automatic

processing is comparable to previous studies using visually selected cloud-free data and a much smaller number of validation samples (Odermatt et al., 2010).

Of the 2291 MERIS images available for Lake Geneva, 1053 contained no applicable pixels. Four images were excluded as outliers due to extraordinarily high CHL, leaving 1234 applicable images, with up to 623 valid observations per grid cell. Grid cells with less than 300 valid observations are found along the shore due to occasional land and mixed pixel flagging. They were removed entirely from further analysis (Kiefer et al., 2015).

2.3 Lake *in-situ* data

2.3.1 Wind

Meteorological data was obtained from the Swiss Federal Office of Meteorology and Climatology, MeteoSwiss. Measurements of wind speed and direction are available every 10 minutes at the station in Pully (Figure 2) for the observed time period of 2002 to 2012. Output from a horizontal 2.2 km meteorological model (COSMO-2; Hug et al. 2010) is also used to account for the spatial heterogeneity of the wind field over Lake Geneva (Lemmin and D'Adamo, 1997).

2.3.2 Lake monitoring profiles

Water samples were taken on a bimonthly to monthly basis at 20 different depth levels (0, 2.5, 5, 7.5, 10, 15, 20, 25, 30, 35, 50, 100, 150, 200, 250, 275, 290, 300, 305 and 309 m) during measurement campaigns of the *International Commission for the Protection of the Water of Lake Geneva* (CIPEL) at SHL2 (Figure 2) in the middle of the lake (46.453 °N, 6.588 °E; 309 m depth). Concentration of bio-available orthophosphates PO₄-P was determined at each depth

217 (Figure 4) and CHL (Figure 3) was extracted by spectrometric analysis from water samples in
218 the top 30 m (Leboulanger, 2003). Water temperature was also monitored by CIPEL on a
219 monthly to bimonthly basis in parallel to the water samples, with a multiparameter profiler.
220 Hourly temperature data were collected at the northern part of the Lake (Buchillon, WGS84
221 46.458 °N, 6.399 °E; Figure 2) at 1 m and 36 m below the surface.

222 **2.4 Model data**

223 The hydrodynamics of Lake Geneva is simulated with the three-dimensional (3D)
224 Delft3D-Flow model version 4.0001. This model was already successfully applied to Lake
225 Geneva by Razmi et al. (2013, 2017). The model solves the Reynolds-Averaged Navier-Stokes
226 equation with the Boussinesq approximation (e.g. fluid incompressible with properties
227 decomposed into their temporal average and their fluctuating component). We use the k-epsilon
228 model as turbulence closure and run the model with a 30 s time step. We use a horizontal (Z-
229 grid) coordinate system with a varying horizontal grid of a resolution never exceeding 300 m
230 horizontally and with the vertical layer thickness increasing from 0.25 m at the surface to 1 m at
231 50 m depth and 10 m at 300 m depth (100 layers). The model is forced by the regional
232 meteorological model COSMO-2 (MeteoSwiss) with a grid size of 2.2 km. A validation example
233 of the hydrodynamic model using high resolution temperature data and data from acoustic
234 Doppler current profilers is shown in Appendix A. The surface temperature outputs from the
235 model are also compared with LSWT from AVHRR. One difficulty in modelling Lake Geneva is
236 the weak stratification in the deepest layers that are not necessarily mixed every winter
237 (Schwefel et al., 2016). This deep convective mixing remained challenging to reproduce
238 (Gaudard et al., 2017). To avoid any cumulative effects in modelling the thermal structure of
239 Lake Geneva, the model was restarted after each deep winter mixing with initial conditions

based on observed temperatures from late-winter. In this study the effects of tributaries were neglected. With a residence time of 11 years, the thermal structure and dynamics of the circulation is only very locally affected by the tributaries (mostly the Rhône River). Moreover, the effects of the Rhône River near the surface are very limited as the river is generally denser (high particle concentration and cold temperature) than the lake surface water and plunge to greater depth (Bouffard and Perga, 2016; Råman Vinnå et al., 2018).

2.5 Spatial correlation statistics

2.5.1 Data-pairs of surface temperature and chlorophyll

Figure 5. Workflow for the post-processing of the remote sensing images (CHL above; LSWT below) and the setup of the CHL-LSWT pairs of the images.

The data-pair processing workflow is depicted in Figure 5. Correlation between LSWT (AVHRR) and CHL (MERIS) images are determined by comparing 450 same-day data pairs as well as pairs with various temporal offsets (the LSWT image up to four days prior to the CHL image (Figure 5). In order to obtain a consistent pixel size between the two datasets, LSWT is resampled onto the reference coordinate grid of the MERIS data by a nearest neighbour (NN) point extraction.

258

259 2.5.2 Moran's I analysis

260 The analytic comparison of LSWT and CHL concentrations from the same day is
261 approached by means of a spatial clustering analysis. The univariate Moran's I (Moran, 1950) is
262 an indicator of the degree of spatial autocorrelation of a given parameter. High Moran's I values
263 refer to "the presence, absence, or degree of a certain characteristic affecting the presence,
264 absence, or degree of the same characteristic in neighbouring units" (Congalton, 1991). In this
265 study, we use the bivariate Moran's I which allows to use two variables (CHL and LSWT). In
266 that case, the value of the first parameter, CHL, in pixel i is compared to the value of the second
267 parameter, LSWT, in all its pixels j .

268

$$269 \quad I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (CHL_i - \overline{CHL})(LSWT_j - \overline{LSWT})}{\sqrt{\sum_i (LSWT_i - \overline{LSWT})^2} \sqrt{\sum_i (CHL_i - \overline{CHL})^2}} \quad (\text{Eq. 1})$$

270

271 Whereas N is the total number of pixels in each image, w_{ij} is the weight given to each individual
272 pixel pair. All pixels that are taken into account as neighbours have the same weight (a fraction
273 of 1) and all other pixels have a weight of 0. The sum of all weights is $\sum_i \sum_j w_{ij} = 1$. $\overline{CHL}$ and
274 $\overline{LSWT}$ are the respective arithmetic means of all values in the considered image pair. The
275 computation was carried out for all product pairs, and repeated for eight neighbourhood ranges
276 including the 4 to 440 NN pixels (Table 1). The variation in the number of NN allows comparing
277 the spatial extent of the correlation, with areas varying from 0.29 km² (NN = 4) to 32.08 km²
278 (NN = 440).

279 **Table 1:** Number of nearest neighbours (NN) used in the weight file of the computation of
 280 Moran's I and their corresponding lake surface area.

Number of NN	Surface covered by the included pixels (km ²)
0	0.00
4	0.29
8	0.58
24	1.75
48	3.50
80	5.83
120	8.75
224	16.33
440	32.08

281

282 Values of I between 0 and +1 indicate a positive spatial correlation with respect to the
 283 neighbourhood range. Practically, higher CHL value pixels are surrounded by higher LSWT
 284 value pixels for a given image pair. Negative I , between -1 and 0, indicate a negative spatial
 285 correlation, where neighbouring values tend to have opposite variations. Practically, pixels with
 286 higher CHL values are surrounded by pixels of lower LSWT values and vice versa. Values close
 287 to zero indicate that there is no significant structure. Significance of the spatial correlation is
 288 tested by randomization (using 999 permutations), comparing the estimation of the expectation
 289 value of Moran's I for random spatial distributions with the obtained result. Only results with $p <$
 290 0.05 are considered. All calculations were performed using the Python package PySAL (function
 291 `pysal.esda.moran.Moran_BV`; Rey, 2015).

3. Results

3.1 CHL and LSWT correlations

The spatial correlation between image pairs of CHL and LSWT varied from a Moran's I of -0.8 to +0.7, e.g., CHL peaks correlated with either colder or warmer surrounding LSWT. Over the 10-year period, eight out of the top ten positive events occurred in spring (Table 2). Similarly, nine out of the top ten (Table 2) negative spatial correlations occurred in summer or in the beginning of autumn. This correlation analysis suggests a seasonal variability in CHL dynamics with mostly positive correlation with LSWT in spring and negative in summer and autumn.

Table 2: Dates of the ten highest positive (left) and ten lowest negative (right) Moran's I for data pairs of CHL and LSWT.

Date	Moran's I	Date	Moran's I
06 April 2010	0.71	09 September 2011	-0.81
20 October 2007	0.68	10 September 2009	-0.80
05 April 2010	0.68	13 October 2011	-0.80
11 April 2010	0.66	26 April 2011	-0.79
22 March 2011	0.55	23 July 2008	-0.70
25 April 2007	0.52	31 July 2007	-0.65
21 March 2011	0.52	18 August 2007	-0.59
24 April 2009	0.50	01 June 2005	-0.58
10 September 2011	0.49	27 July 2007	-0.57
29 May 2010	0.49	01 September 2010	-0.55

3.1.1 Seasonal trend

The monthly ratio (R) between the number of positive and negative values for Moran's I of the image pairs provides a straightforward synthesis of the temporal dynamics in the correlation between CHL and LSWT (Figure 6). A R ratio larger than (respectively lower than) 1

308 indicates monthly dynamics dominated by positive (respectively negative) correlations between
 309 CHL and LSWT. As expected, based on the dynamics of stratification and nutrient limitation, all
 310 data show $R > 1$ in March and April, and $R < 1$ later in the year.

311

312 **Figure 6.** Ratio of the number of positive to negative Moran's I results (4 NN) per month for
 313 different temporal offsets. The dotted line (ratio = 1) indicates equal positive / negative numbers.

314 3.1.2 Correlation for different temporal offsets

315 Deriving Moran's I for data pairs of different temporal offsets allows for including some
316 of the temporal correlation range and hence for the inference of causative processes. Correlations
317 at no or at short time offsets are expected to represent vertical or horizontal advection of water
318 with CHL being temporarily relocated close to the surface and becoming accessible by remote
319 sensing techniques. Correlations at a larger temporal offset are likely to represent phytoplankton
320 growth resulting from lateral or vertical advection of any limiting compounds like nutrients. The
321 intensity value of R (Figure 6) is most pronounced for data pairs with one and two days offset.
322 After three days, the ratios in spring (March and April) remain above 1, while the trend in the
323 ratio approaches 1 from May to September for three or four days of temporal offset.

324 3.1.3 Spatial correlation for different lateral extents

325 Deriving Moran's I with different lateral extents (different numbers of NN) allows
326 examining the horizontal size of the observed pattern. The sign of Moran's I does not change
327 when increasing the number of NN (Figure 7) and positive results for 4 low NN remain positive
328 for large 440 NN. The values, however, decline slightly when taking larger surface extents into
329 account, indicating a decrease of correlation when moving further away from the point of
330 comparison (central CHL pixel). Correlation remains typically high until $NN \approx 80$ corresponding
331 to an area of 5.9 km^2 . When analysing this correlation for different CHL concentration in the
332 lake (Appendix B), we observe that correlation extends over larger areas when CHL is high, but
333 smaller extent for weak CHL.

334

335 **Figure 7.** Moran's I for 4 to 440 NN. Dates correspond to those of Figures 9 and 10.

336 In conclusion, the statistical analysis suggests: (i) a seasonal variability in the correlation
 337 between CHL and LSWT, (ii) the strongest correlation with an offset of 1 or 2 days between
 338 CHL and LSWT, unfortunately preventing a statistical distinction between CHL growth and
 339 transport, and (iii) lateral horizontal correlation scales that suggest hydrodynamic drivers playing
 340 a key role for the often horizontally limited phytoplankton abundance. We therefore investigate
 341 the influence of the wind as the main external force driving lake dynamics and potentially
 342 responsible for the spatial variability.

343 3.2 Influence of the wind on lake dynamics

344 The effect of the wind on the correlation between LSWT and CHL was tested by
 345 comparing the statistical Moran's I correlation to a non-dimensional wind ratio. This wind ratio
 346 scale was constructed as the ratio between the three-days average wind intensity prior to the
 347 LSWT acquisition and the three-days average wind recorded at the MeteoSwiss station in Pully
 348 over the entire ten years considered. The three-days window length was chosen to be close to the
 349 longitudinal basin-scale internal wave period for Lake Geneva (Bouffard and Lemmin, 2013).

350 Correlation data were split into two subsets, for spring and summer correlation, respectively, as
 351 defined above.

352 Spring correlations do not show any significant relationship of Moran's I correlation with
 353 wind (Figure 8). We observed highly correlated images following both high and low wind
 354 intensity. The summer cases are more instructive. As shown in Figure 8, highly (negative)
 355 correlated images followed above-average wind strengths in summer.

356

357 **Figure 8.** Bin averaged absolute Moran's I as a function of the wind ratio. Wind ratio is defined
 358 as the ratio between the wind averaged over the three-days prior to the satellite image to the
 359 wind averaged over ten years. High Moran's I in summer are associated with high winds.

360 A mechanistic evaluation of the correlation between LSWT and CHL requires more
 361 information on the spatial and temporal dynamics of lake temperature and CHL. Wind analysis
 362 already suggested at least three cases depending on the wind intensity and the period of the year
 363 (case 1: high wind in spring; case 2: high wind in summer; case 3: low wind). We investigated
 364 the first two cases by means of *in-situ* measurements, satellite data, and hydrodynamic
 365 modelling. The latter case 3 is not further reported in this study because forcing becomes more
 366 complex at low wind speeds.

367 3.2.1 Case 1. High wind prior to high image pair correlation in spring

368 The period of 21/22 March 2011 corresponds to this case. Images have a high positive
369 Moran's I correlation of 0.52 and 0.55 (Table 2) and are following a strong north-east wind event
370 (Figure 9a) on 19 and 20 March. Both LSWT from satellites and model data show the same
371 pattern with colder surface water in the western part of the lake center and warmer water on both
372 western and eastern end (Figures 9cd). This observation is in good agreement with the
373 thermocline being close to the surface at the lake center and being strongly lowered on both ends
374 (Figure 9f). This downwelling structure on both ends of the basin is explained by the spatially
375 heterogeneous wind structure (Figure 9e). The strong north-east wind is likely perturbed by the
376 local topography of the surroundings of the lake, with the steep Alpine mountain slopes south of
377 the lake. As a consequence, part of the northern wind field on the eastern part of the lake is
378 deviated towards the east (Figure 9e) leading to a second smaller unexpected downwelling zone
379 in this area. This example suggests that in spring, downwelling areas can lead to high CHL near
380 the lake surface (Figure 9b).

Figure 9. a) Wind magnitude and direction. Shaded area represent the investigated day with LSWT and CHL satellite data. b) CHL satellite image for 21 March 2011 (left) and 22 March 2011 (right). c) LSWT satellite image for 21 March 2011 (left) and 22 March 2011 (right). d) LSWT modelled for 21 March 2011 (left) and 22 March 2011 (right). e) Wind magnitude (colour-coded) and direction (arrows) for 20 March 2011. Data from COSMO-2 meteorological model; f) Longitudinal transect of temperature over the water column for day 20 March 2011 extracted from the hydrodynamic model.

3.2.2 Case 2. High wind prior to high image pair correlation in summer

The period of September 2011 corresponds to this case. The AVHRR and MERIS images from 9 September have a large negative Moran's I correlation of -0.81 (Table 2; Figures 10bcfg) and is following strong winds from the south-west over the previous three days.). The previous image pair from 30 August shows an almost homogenous horizontal CHL distribution while the three following image pairs (9, 10 and 13 September, Figures 10bcfg) indicate higher CHL in the Petit Lac of Lake Geneva.

The qualitative agreement between AVHRR data and the hydrodynamic model is excellent, but – comparing the two – we noticed small horizontal offsets (~250 m) between warm and cold areas (Figures 10cdgh). However, compared to the lake size (length: 74 km), this is small enough to allow a comparison between the satellite and model data. Time series of surface temperature data in Buchillon (Figure 2) show a very good agreement between satellite, model and *in-situ* data (Figure 10k).

On 9 / 10 September 2011, the lake surface is significantly colder in the western part (Petit Lac) and on the north-western part of the Grand Lac (Figures 10cdgh). The thermocline excursion extracted from the 3D model suggests that these areas correspond to strong upwelling zones where the thermocline almost reaches the surface on the 9 of September 2011 (Figure 10e). This upwelling is also clearly noticeable on a longitudinal transect (Figure 10j). This

408 second example suggests that in summer, strong wind-induced upwelling can lead to high CHL
409 near the lake surface (Figures 10 bf).

412 **Figure 10.** a) Wind magnitude and direction. Shaded area represent the investigated day with
 413 LSWT and CHL satellite data. b) CHL satellite image for 30 August 2011 (left) and 09
 414 September 2011 (right). c) LSWT satellite image for 30 August 2011 (left) and 09 September
 415 2011 (right). d) LSWT model data for 30 August 2011 (left) and 09 September 2011 (right). e)
 416 modelled thermocline depth for 30 August 2011 (left) and 09 September 2011 (right). j)
 417 Longitudinal transect of temperature over the water column for day 08-09-2011. f) - i) same as
 418 b) - e) but for the days 10 September 2011 (left) and 13 September 2011. k) Time series of in-situ
 419 (red line, 1 m depth; black line, 36 m depth), modelled temperature (blue line, 1 m depth), and
 420 remotely sensed LSWT (green dots).

421

422 **4 Discussion**

423 **4.1 Spring correlation**

424 The analysis of CHL and LSWT image pairs has pointed out different correlations depending
 425 on the season. Spring phytoplankton growth appears here temperature-limited. Warmer zones of
 426 the lake show enhanced CHL and the correlation between the two parameters is positive for all
 427 temporal offsets. Most of the top positive Moran's I are observed during spring. In the case of
 428 Lake Geneva, the absolute level of LSWT in springtime may be less critical for algal growth
 429 than the surface layer stratification and implicitly the water column stability. Depending on the
 430 phytoplankton species, a stratified water column is needed to allow these organisms to stay in the
 431 photic layer. The onset and strength of stratification is not uniform over the whole lake, warmer
 432 zones in spring indicate areas where the surface layer is already more stable. Taylor and Ferrari
 433 (2011) found that a bloom developed due to the start of net warming, weakening turbulent
 434 mixing, and a subsequent increase in the residence time of phytoplankton cells within the
 435 euphotic layer. Ferreira et al. (2015) support these findings, stating that among several active
 436 mixing models for North Atlantic there was a bias towards mechanisms involving heat flux. The
 437 detailed example of March 2011 shows two downwelling regions associated with high CHL.

438 Downwelling regions and associated warmer surface water with pronounced stratification are
439 therefore found to be hot spots for spring algae growth in Lake Geneva.

440 **4.2 Summer correlation**

441 From the bi-monthly *in-situ* measurements at location SHL2 (Figure 2) it can be observed
442 that the CHL maxima in Lake Geneva are at ~3 to 5 m depth in March and April, and gradually
443 move to ~8 to 10 m depth by late summer. This phenomenon is linked to the deepening of the
444 stratification and to the vertical structure of depleted nutrients in the photic zone (Anneville et
445 al., 2002). From a uniformly distributed phosphate concentration after winter convective mixing
446 (Figure 4), this component gets quickly depleted at the surface as biological activity sets in.
447 From a temperature-limited phytoplankton growth in spring, the lake turns to a nutrient-limited
448 growth in summer. By temperature-limited phytoplankton growth, we therefore include the
449 contribution from the absolute temperature as well as the light limitation related to the build-up
450 of thermal structure. The spring stratification and modifications of the turbulence level can
451 maintain certain phytoplankton for longer in the photic zone and thereby reduce the light
452 limitation which remains a strong constraint in winter and spring. The combination of remote
453 sensing observations with hydrodynamic and eventually biogeochemical models provide an
454 efficient tool to investigate the mechanisms responsible for spring blooms in lakes.

455 Such a nutrient-limited structure is apparently consistent with observations of enhanced
456 CHL in colder upwelling zones during the summer months. The first hypothesis is that upwelled
457 nutrient-rich, colder water from deeper layers is responsible for phytoplankton growth in the
458 photic layer during that season. The 1-2 days shift for the highly negative correlation between
459 CHL and LSWT pleads also for a rapid growth of algae following nutrient uptake by upwelling
460 events. However, the summer deep CHL maximum in Lake Geneva is often at depths that

461 contribute only a minor part to the water-leaving radiance signal (Kiefer et al., 2015). Therefore,
462 it may remain unnoticed by remote sensing observation until an upwelling mixes it with colder
463 water from below and conveys it towards the surface, where it becomes measurable for remote
464 optical sensors. Such a second hypothesis of near-surface pseudo algae blooms were previously
465 observed in the Experimental Lakes (Fee, 1976), where not only nutrients, but also deep
466 phytoplankton were brought to the surface by upwelling and mixing events.

467 As the satellite data in the visible range are still relatively sparsely, though, we cannot
468 quantitatively assess the role of upwellings as supplier of deep nutrients or phytoplankton to the
469 surface. Typically, it takes one to three days for nutrients to be incorporated into biomass by
470 growth (Reynolds and Irish, 1997), and this time remains shorter than the typical revisiting time
471 of MERIS. An immediate increase in CHL after upwelling would therefore indicate a
472 redistribution of phytoplankton along the water column, rather than a redistribution of nutrients
473 and a consequent growth of phytoplankton in the epilimnion. We finally try to distinguish
474 between upward transport of already existing deep CHL maximum or nutrients into the surface
475 layer by investigating the remote sensing data with respect to the basin-scale internal wave
476 oscillation following the first wind-induced upwelling-downwelling inferred from high temporal
477 resolution 3D hydrodynamic modelling.

478 **4.3 Role of basin-scale internal waves**

479 An analysis of the 3D hydrodynamic model for the period of September – October 2011
480 indicates that the lake dynamics is driven by a characteristic basin-scale internal wave. We show,
481 based on basin-scale internal wave isotherm vertical dislocations (Figure 11), that the
482 investigated LSWT – CHL correlation in September 2011 results from an upward transport of
483 the deep CHL maximum. The two consecutive CHL images on 9th and 10th September 2011 are

484 particularly meaningful. After the wind-induced upwelling on 7th and 8th of September, we
485 observe a negative correlation with cold surface temperature and elevated CHL in Petit Lac on
486 the 9th of September. However, the satellite image indicates almost no near surface CHL on the
487 next day (10th of September) except at the very western end. On this day, the Petit Lac thermal
488 structure corresponds to a downwelling situation and we observe a weak upwelling area at the
489 southern shore of the Grand Lac. This upwelling/downwelling feature travelling up to 2/3 of the
490 longitudinal distance of Lake Geneva with an anticlockwise circulation is the typical signature of
491 an internal Kelvin wave with a period of 3.5 days for late summer (Bouffard and Lemmin, 2013).
492 Kelvin waves are common features as can be seen with the two consecutive peaks observed in
493 the temperature time series at 36 m depth (Buchillon, Figure 10). The anticlockwise Kelvin wave
494 motion of the investigated period is shown in Figure 11 from the detrended temperature
495 oscillation at 20 m depth (thermocline). We note a second passage of Kelvin waves in the Petit
496 Lac on the 12th and 13th of September associated with downwelling. This second passage is
497 shown by the MERIS data as an increase in CHL on the 12th (not shown) and the 13th September
498 2011 (Figure 10). The following MERIS images in September and October 2011 do not show
499 any near-surface CHL enhancement (not shown). We conclude from this coupled 3D modelling
500 and remote sensing study that the summer negative correlation in LSWT and CHL can be
501 associated with wind-induced basin-scale internal waves (e.g. Kelvin waves) pushing the
502 thermocline upward, thereby transporting temporarily the deep CHL maximum close to the
503 surface.

Figure 11. Detrended modelled temperature time series at 20 m depth on three control points across the lake. Data have been offset vertically by 5 °C (East control point) and 10 °C (North control point). The ~3.5-day oscillation corresponds to a Kelvin wave with cyclonic propagation along the shore.

5 Conclusion

Remotely sensed surface temperature (LSWT) and chlorophyll images (CHL) of a large lake show sequences of intriguing positive and negative correlations (Figure 1). We used *in-situ* data, remote sensing data, and three-dimensional (3D) hydrodynamic modelling to investigate their relationship. Two types of correlations between LSWT and CHL were observed with mostly positive correlation in spring and negative correlation in summer and autumn. In spring, we observed elevated correlation both under windy and calm conditions. In summer and autumn, strong negative correlations were following an episode of increased wind intensity in the days preceding the image pair. Spring positive correlation indicates that CHL growth is temperature-related. We identified downwelling zones associated with higher CHL than in the rest of the

lake. The increase of CHL resulted from warmer surface temperature and/or stronger stratification in the downwelling zone. Summer and autumn negative correlation were associated with upwelling zones and colder surface water. Two driving mechanisms were investigated as cause of increased CHL in these regions: (i) upwelling bringing nutrients to the photic zone, and (ii) upwelling transport and mixing of deep CHL maxima of the photic zone to the lake surface. The analysis of remotely sensed CHL images based on basin-scale internal wave dynamics suggests that in the deep large Lake Geneva, negative summer and autumn correlations result from the deep CHL maxima being upwelled close to the surface and becoming accessible to satellite observations.

From a remote sensing point of view, special care should be taken on the data interpretation of summer and autumn algae blooms in deep large lakes. This study suggests that some of the blooms are in fact the signature of deep CHL maxima temporarily moved up near the surface by large internal wave motions. Recent satellites with shorter revisiting times and smaller pixel resolutions, such as Sentinel-2 and Sentinel-3, will provide new remotely sensed information to analyse the dynamics of lake ecosystems at unprecedented temporal and spatial scales

The coupling between *in-situ* data, remote sensing observations, and hydrodynamic modelling was shown to provide insightful results, each information source being able to compensate for the weakness of other data sources. Further studies should focus on a deeper integration of the information sources.

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702 Figure legends

703 **Figure 1.** Differences of chlorophyll (CHL) and lake surface water temperature (LSWT) relative
704 to their spatial averages for two same-day scenes, one in spring and one in autumn 2011. Both
705 show a positive spatial correlation between CHL and LSWT.

706 **Figure 2.** Map of Lake Geneva with locations SHL2 (pink), Buchillon (green) and Pully
707 (yellow). In-situ CHL calibration samples are regularly taken at SHL2. Temperatures measured
708 at Buchillon and at SHL2 have been used for calibrating the three-dimensional Delft3D-Flow
709 model. 20 m isolines are shown.

710 **Figure 3.** Concentrations of CHL during the productive season (March to October) in Lake
711 Geneva. The data shown is based on bi-monthly *in-situ* measurements at position SHL2 (Figure
712 2) for the period 2002-2012. Boxplot with whiskers length $1.5 (\pm 2.7 \sigma)$; outliers are not shown.

713 **Figure 4.** a) Average annual cycle of phosphate concentrations at different depths (0-5 m, 35 m,
714 50 m, 100 m) for the time 2002 to 2010. Dashed line: average per day of the year; solid line: five
715 data points running mean (corresponding to ~ 12 days). b) Average annual cycle of LSWT,
716 computed from AVHRR satellite images (2002-2012) and averaged over the whole lake. Dashed
717 line: average per day of the year; solid line: 10 days running mean.

718 **Figure 5.** Workflow for the post-processing of the remote sensing images (CHL above; LSWT
719 below) and the setup of the CHL-LSWT pairs of the images.

720 **Figure 6.** Ratio of the number of positive and negative Moran's I results (4 NN) per month (x-
721 axis) for different temporal offsets. The dotted line (ratio = 1) indicates equal numbers.

722 **Figure 7.** Moran's I for 4 to 440 NN. Dates correspond to those of Figures 9 and 10.

723 **Figure 8.** Bin averaged (every 0.1) absolute Moran's I as a function of the wind ratio. Wind ratio
724 is defined as the ratio between the wind averaged over the three day prior to the satellite image to
725 the wind averaged over ten years. High Moran's I in summer are associated with high winds.

726 **Figure 9.** a) Wind magnitude and direction. Shaded area represent the investigated day with
727 LSWT and CHL satellite data. b) CHL satellite image for 21 March 2011 (left) and 22 March
728 2011 (right). c) LSWT satellite image for 21 March 2011 (left) and 22 March 2011 (right). d)
729 LSWT model data for 21 March 2011 (left) and 22 March 2011 (right). e) Wind magnitude
730 (colour-coded) and direction (arrows) for 20 March 2011. f) Longitudinal transect of temperature
731 over the water column for day 20 March 2011.

732 **Figure 10.** a) Wind magnitude and direction. Shaded area represent the investigated day with
733 LSWT and CHL satellite data. b) CHL satellite image for 30 August 2011 (left) and 09
734 September 2011 (right). c) LSWT satellite image for 30 August 2011 (left) and 09 September
735 2011 (right). d) LSWT model data for 30 August 2011 (left) and 09 September 2011 (right). e)
736 modelled thermocline depth for 30 August 2011 (left) and 09 September 2011 (right). j)

737 Longitudinal transect of temperature over the water column for day 08-09-2011. f) - i) same as b)
738 - e) but for the days 10 September 2011 (left) and 13 September 2011. k) Time series of *in-situ*
739 (red line, 1 m depth; black line, 36 m depth), modelled temperature (blue line, 1 m depth),
740 remotely sensed LSWT (green dots).

741 **Figure 11.** Detrended model temperature time series at 20 m depth on three control points across
742 the lake. Data have been offset vertically by 5 °C (East control point) and 10 °C (North control
743 point). The ~3.5-day oscillation corresponds to a Kelvin wave with cyclonic propagation along
744 the shore.

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Appendix A

Data sources and hydrodynamic lake model

We used the Delft3D-Flow as three-dimensional (3D) hydrodynamic model with a $k-\epsilon$ turbulence closure. River inflows and outflows were not implemented in this study and the forcing was solely at the air–water interface. The forcing data includes wind intensity and direction, solar radiation, air temperature, cloud coverage, relative humidity and atmospheric pressure provide at hourly time steps from a meteorological model COSMO-2. For this study, only wind forcing was treated as a space varying parameter and all other forcings were extracted from a grid cell in the middle of the lake. The model constant used in the model are summarized in Table A1.

For the year 2011, we have validated the model with bi-monthly temperature profile at the lake center (SHL2), hourly temperature measurements at 1 m and 36 m below the surface offshore Buchillon (Figure 2), 297 AVHRR LSWT data (with cloud cover lower than 50%) and acoustic Doppler current profilers. Figure A1 provides an overview of the validation and the different root mean square errors are indicated in Table A2.

From a lake functioning perspective, a better integration of in-situ and remotely sensed observation into models, for instance, through data assimilation, will provide better estimates of the parameters over time and, more importantly, a quantification of uncertainties.

Figure A1. Examples of validation of the model. a) Comparison between the AVHRR LSWT and the model LSWT on day 5 July 2011. The horizontal structures are reproduced by the model. Other comparisons can be found on Figs. 9-10. b) Time series of observed and modelled temperature at 1 m and 36 m below the surface offshore of Buchillon. c) Time series of observed and modelled current intensity. d) Bi-weekly time series of observed and modelled temperature at the lake center. RMSE are provided on Table A2.

Table A1: Parameters used in the three-dimensional hydrodynamic model.

Parameter	Name	Value
$\nu_H [\text{m}^2 \text{s}^{-1}]$	Background horizontal eddy viscosity	1.0
$\nu_V [\text{m}^2 \text{s}^{-1}]$	Background vertical eddy viscosity	0

$D_H [\text{m}^2 \text{s}^{-1}]$	Background horizontal eddy diffusivity	1.0
$D_V [\text{m}^2 \text{s}^{-1}]$	Background vertical eddy diffusivity	5.0×10^{-7}
$z_{Sec} [\text{m}]$	Secchi depth	5
$k_S [\text{m}]$	Bottom roughness	5.0×10^{-2}
$c_H [-]$	Stanton number	5.0×10^{-3}
$c_e [-]$	Dalton number	1.5×10^{-6}

777

778 **Table A2:** RMSE between observation and model.

Location	SHL2	Buchillon	Buchillon	Entire Lake	Buchillon
Deployment	Multiparameter probe (water column)	Mooring (1 m)	Mooring (36 m)	Satellite (surface)	ADCP mooring (water column)
Parameter	Temperature	Temperature	Temperature	Temperature	Current velocity
Units	(°C)	(°C)	(°C)	(°C)	(m s ⁻¹)
RMSE	1.9	0.7	1.1	1.5	0.05

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781 **Appendix B**

782 **Spatial correlation without temporal offset**

783 The analysis of CHL and LSWT pairs with low average CHL concentrations ($< 6 \text{ mg m}^{-3}$,
784 first graph of Figure B1, all NN and 0 offset) indicates slightly positive average Moran's I in
785 early spring and negative between May and October. The average Moran's I for data pairs
786 representing intermediate CHL (6 to 12 mg m^{-3}) indicates a strong positive correlation in March,
787 but no clear temporal patterns for the following months. In contrary, high CHL data pairs (CHL
788 $> 12 \text{ mg m}^{-3}$), reveal a consistently decreasing average Moran's I in the course of the year.

790 **Spatial correlation with temporal offset**

791 The monthly averages of Moran's I are more pronounced for data pairs with one or two
792 days of difference (i.e. LSWT preceding CHL; Figure B1, D-F)). The reaction of the
793 phytoplankton on nutrient concentration variations may be better captured after some temporal
794 offset, even for low CHL average concentrations. Again, Moran's I is decreasing between spring
795 and summer from positive correlation in spring to negative correlation in summer. The signal is
796 again generally stronger for higher CHL concentrations (Figure B1, D), 3rd graph). The effect of
797 the spatial extent of the included NN on the correlation, however, is not homogenous anymore
798 (2nd graph of E) and F), Figure B1). It appears that for a certain temporal offset between CHL
799 and LSWT, the spatial extent of the phenomenon decreases. Whereas for same-day data pairs the
800 results between different NN numbers were very similar, considerable differences are found
801 here.

802 For three and four days of difference between the LSWT and the CHL data and low CHL
803 content (Figure B1, G)), the evolution during the productive season is similar to the previous
804 results. Positive values are found for March and April, after which the values become negative
805 but stay close to zero. Just like for data with one to two days between LSWT and CHL
806 observations, differences are found between small and large spatial extents (H) and (I).

Figure B1. Boxplots showing all results of Moran's I of LSWT and CHL image pairs, with different temporal offsets on the x-axis (0 days, 1 & 2 days, 3 & 4 days) as well as different spatial extents on the y-axis (all NN, low NN and high NN).