Chapter

The Color of Water from Space: A Case Study for Italian Lakes from Sentinel-2

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Abstract

Lakes are inestimable renewable natural resources that are under significant pressure by human activities. Monitoring lakes regularly is necessary to understand their dynamics and the drivers of these dynamics to support effective management. Remote sensing by satellite sensors offers a significant opportunity to increase the spatiotemporal coverage of environmental monitoring programs for inland waters. Lake color is a water quality attribute that can be remotely sensed and is independent of the sensor specifications and water type. In this study we used the Multispectral Imager (MSI) on two Sentinel-2 satellites to determine the color of water of 170 Italian lakes during two periods in 2017. Overall, most of the lakes appeared blue in spring and green-yellow in late summer, and in particular, we confirm a blue-water status of the largest lakes in the subalpine ecoregion. The color and its seasonality are consistent with characteristics determined by geomorphology and primary drivers of water quality. This suggests that information about the color of the lakes can contribute to synoptic assessments of the trophic status of lakes. Further ongoing research efforts are focused to extend the mapping over multiple years.

Keywords: chromaticity, multispectral sensors, optical remote sensing, inland waters, mapping, Sentinel-2, Italy, lakes

1. Introduction

Freshwater constitutes only 3% of the Earth's water resource, but only 1% is available as surface water in lakes and rivers, while the remainder is frozen in glaciers and ice caps or stored underground. Lakes represent a valuable source of water for consumption and irrigation and provide a variety of key services such as food provision, energy generation, transportation, recreation, and tourism. Lakes are essential components of the hydrological and biogeochemical cycles due to their basic ability to store, retain, clean, and provide water [1]. Lake waters also contribute to support the agricultural sector and livestock to feed the 7 billion of people on our planet [2].

Lake ecosystems are under pressure from various human impacts as well as climate change [3]. They are sensitive to a range of stressors operating at global, regional, and local scales [4] whose impacts manifest in eutrophication, proliferation of toxic algae, increase in turbidity, loss of aquatic benthos, and harmful effects on health for both animals and humans [5]. Significant effort is often devoted to monitor for changes, to the restoration of impacted systems, and to the preservation of healthy lakes. For example, in Europe, the need for having "[…] a coherent and comprehensive overview of water status within each river basin district" was defined by the Water Framework Directive (WFD) [6], setting out the requirements for the monitoring of the status of surface waters with the main objective of maintaining "good" and non-deteriorating status for all waters.

Earth observation (EO) techniques with optical sensors have been used for many decades to support timely and frequent acquisition of synoptic lake water quality information [7 and reference herein]. In recent years, EO has become an operational tool to support traditional measurements providing, at a relatively low cost and for some bio-geophysical parameters, information on surface water status to support a variety of applications [e.g., 8, 9]. EO systems measuring water quality typically are multispectral radiometers which might be grouped by their characteristic spatial and spectral resolution. Spatial resolution (the area on the ground covered by each pixel) is of particular importance for remote sensing of inland waters [10] as it determines the minimum size of lakes visible by each satellite. Four groupings of satellite sensors can currently be distinguished: ocean color (e.g., Sentinel-3 OLCI or MODIS, with pixels of about 300–1000 m), multispectral sensors (e.g., Landsat or Sentinel-2, with pixels of 10–30 m), imaging spectrometers (e.g., Hyperion or PRISMA, with a pixel size of 30 m, but coverage is not global unlike the previous missions), and geostationary platforms (e.g., GOCI, with a 500 m pixel size). Ocean color sensors provide better data for aquatic applications because they have more and narrower spectral bands and higher signal-to-noise ratios, but multispectral sensors are often the only choice for inland water applications because their finer spatial resolution can resolve smaller water bodies [10]. Multiple sensors might be used for improving the resolutions as in [11].

After processing of the light measured by a satellite sensor at the top of the atmosphere by removing light scattered by the atmosphere, stray light from adjacent pixels and specular reflection from the water surface physical and biochemical parameters of lakes can be estimated using several methods. Parameters that can be estimated include turbidity, photosynthetic biota (e.g., phytoplankton, macrophytes, and cyanobacteria), colored dissolved organic matter (CDOM, e.g., humic and fulvic substances), and suspended non-algal particulate matter (e.g., detritus from land). Lakes are complex ecosystems relative to oceanic waters due to the large variety and range of concentrations of living and nonliving material [12]. This complexity also applies to the optical properties, i.e., the spectral characteristics of absorption and scattering of light, of the constituents of lake water [13, 14], and, therefore, their estimation in lakes is extremely challenging. For example, if one component (e.g., CDOM) dominates the others (e.g., phytoplankton), it may mask the signature of the other components in the reflectance spectrum and reduce the accuracy of determining their concentrations. Due to this optical complexity, most algorithms for the retrieval of biogeochemical parameters are tailored to specific lakes and are not applicable to systems with optical properties different to those used for their development [e.g., 15, 16].

When research activities are focusing on mapping water quality in lakes from national to global scales, simpler yet robust approaches might be therefore strategically adopted. Among those, the methods estimating the color of water as perceived by the human eye show promise, because it does not rely on knowledge on inherent optical properties and concentrations of water components. Although perceived color is not unambiguously related to quantitative water quality attributes such as clarity, the phytoplankton, suspended matter, and CDOM, the color of water can be seen as a water quality attribute in its own right with the advantage of intuitive meaning in public perception.

The Commission Internationale de l'Éclairage (CIE) [17] mathematically defines color by weighting the reflectance spectrum of an object with three mixing curves, or chromaticity curves, each specifying the respective sensitivity of the human eye to one of the primary colors. To adapt this definition to the spectral bands of satellite sensors, several methods have been developed starting from the use of Forel-Ule (FU) scale, a historical standard recently recalibrated [18]. More recently, van der Woerd and Wernand [19] developed an algorithm to derive the hue angle consistently from different ocean color and multispectral sensors. Hue angle can be thought of as the pure color most closely resembling the true color of natural waters.

Several studies have used color analysis for a variety of applications in different aquatic ecosystems, including oceans and lakes. For example, [20] used chromaticity coordinates to prove the capability of Landsat-5 in assessing water quality changes from the pelagic to the coastal zone in Lake Garda (Italy). Wang et al [21] assessed the trophic state of global inland waters using a MODIS-derived Forel-Ule index finding that oligotrophic large lakes are concentrated in plateau regions in central Asia and South America, while eutrophic large lakes are concentrated in central Africa, eastern Asia, and mid-northern and southeast North America. In New Zealand, [22] calculate the color of water on almost 45,000 observations from 1486 lakes over 4 years. A preliminary exploratory analysis suggests that both geophysical and anthropogenic factors, such as catchment land use, provide environmental control of lake color and are promising avenues for future analysis. Lastly, [23] revealed that subtropical oceans will get bluer as fewer phytoplanktons are able to survive in its waters, while green regions at the poles will turn greener as warming waters become more habitable for them.

In this study, the method developed in [24] is adopted to calculate the color of Italian lakes based on multispectral Sentinel-2 images, whose 10-m spatial resolution allowed us to observe 170 lakes of the country. We follow [22] to analyze and classify lake colors from two different periods in 2017 for seasonal variations and patterns related to geomorphology and other primary drivers of water quality.

2. Materials and methods

2.1 Study area

About 2000 lakes are known in Italy, and ~500 of those have a surface area greater than 0.2 km^2 (400 of which are freshwater bodies and 100 brackish water bodies) [25]. The lakes are diverse systems with a plethora of values, including biodiversity, water provision, recreation, and landscape. For example, the volcanic-lake district located between Lazio and Basilicata administrative regions has 80% of the deep lakes within the Mediterranean coastal region holding 94% of the freshwater in central and southern Italy [26].

Lakes in Italy have different origins and features. Alpine lakes are generally small, fed by meltwater, and are normally located at altitudes above 2000 m a.s.l. where they occupy basins carved by glaciers. The deep subalpine lakes—the largest in Italy—occupy deep elongated valleys shaped by the erosive action of glaciers during the last glacial period. The debris left by ice on the edge of the plain forms the so-called morainic amphitheaters that, like the case of Lake Garda, still mark the southern limit of these water basins. The moraine lakes are entirely enclosed by hills formed by glacial deposits on the border between the Prealps and the Po Plain (e.g., lakes Viverone, Varese, Pusiano). The barrier lakes are formed following the obstruction of a river valley due to a landslide or the accumulation of alluvial sediments; examples are Lake Alleghe (landslide) and Lake Levico (accumulation of sediments). Volcanic lakes, mainly found in central Italy, feature an almost circular shape. Their formation is mainly related to subsidence and caldera formation during the final stages of volcanic activity [27]; examples are Lake Bolsena and Lake Bracciano. Alluvial lakes located in Central Apennines are formed by the filling of depressions originated by the raising of the Apennine chain (e.g., Lake Trasimeno). Other types of lakes include coastal and artificial ones.

Italy's overall lacustrine water volume is about 146 billion m^3, with seven large lakes (Garda, Maggiore, Como, Bolsena, Iseo, Bracciano, and Monte Cotugno) representing more than 97% of this amount. A major part of these lakes is located in the northern sector of the Italian Peninsula (along the Alpine range), although the Mediterranean regions are characterized by a high number of artificial lakes mainly supporting drinking or irrigation purposes. The morphology of the lakes is diverse with surface areas ranging between 3.4 and 370 km^2 (lakes Comabbio and Garda, respectively), maximum depths ranging between 2 and 410 m (Lesina and Como), and altitudes ranging between 0 and 507 m a.s.l. (lakes Lesina and Varano, and Vico).

Since 1997, a systematic investigation of morphological, physical, chemical, and biological features of the main lakes (with areas >0.2 km^2) has been implemented under the Project LIMNO. This project has the objective of developing a territorial information system for the interdisciplinary study of Italian lake environments. It consists of a database focused on morphometric, chemical, and biological data of water and sediments and the geographic information system tool (GIS LIMNO), which also includes thematic information on land use.

A major outcome of this project is the ability to analyze the physical and chemical variables for time trends in many lakes, especially the subalpine ones. For Lake Pusiano, it was revealed that the total phosphorus (TP) concentration, after having increased up to 200 μg/L (i.e., hypereutrophic) around the middle of the 1980s of the last century, has undergone a constant decline, down to the value of 58 μg/L in 2004. In other cases, however, opposite trends were observed. For example, Lake Garda exhibited TP concentrations in the range of 15 (1990s) to 34 μg/L during the 2004 circulation. In general, TP concentration shows higher values in lakes located at altitudes lower than 1000 m a.s.l. (median = 43 μg/L), while, for high-altitude lakes, this value never exceeds 4 μg/L. A similar trend has been also detected for total alkalinity (TAlk), with the highest values at low-altitude lakes (TAlk = 2.65 meq/L) and lowest values at high-altitude lakes (TAlk = 0.40 meq/L). This trend is also reflected by pH, which shows the minimum values at the highest altitudes. To sum up, the collected evidence has confirmed a considerable reduction in the maximum values of nutrients and contaminants even if data has often verified an increase in their basal levels.

2.2 Sentinel-2 data and processing

Sentinel-2 is a multispectral imaging mission of the Copernicus program. The mission that is funded by ESA Member States and the European Commission consists of twin satellites, the Sentinel-2A and Sentinel-2B, launched on 23 June 2015 on 7 March 2017, respectively.

Sentinel-2A and Sentinel-2B carry the Multispectral Imager (MSI), a push-broom sensor designed and built by Airbus Defense and Space, France. MSI has 13 spectral bands, ranging from the visible to the shortwave infrared (443–2190 nm) [28], with a swath width of 290 km and spatial resolutions of 10, 20, and 60 m (**Table 1**).

	S2A		S2B		
Band number	**Central wavelength (nm)**	**Bandwidth (nm)**	**Central wavelength (nm)**	**Bandwidth (nm)**	**Spatial resolution (m)**
b1	442.7	21	442.2	21	60
b2	492.4	66	492.1	66	10
b3	559.8	36	559.0	36	10
b4	664.6	31	664.9	31	10
b5	704.1	15	703.8	16	20
b6	740.5	15	739.1	15	20
b7	782.8	20	779.7	20	20
b8	832.8	106	832.9	106	10
b8a	864.7	21	864.0	22	20
b9	945.1	20	943.2	21	60
b10	1373.5	31	1376.9	30	60
b11	1613.7	91	1610.4	94	20
b12	2202.4	175	2185.7	185	20

Table 1.
Nominal settings of Sentinel-2A/Sentinel-2B MSI with band number, central wavelength, band width, and pixel size/resolution (source ESA).

By providing spatial resolution on the order of tens of meters and spectral bands comparable to the Operational Land Imager on Landsat 8 (and imagers on previous Landsat missions back to Landsat-5), Sentinel-2 is becoming to be considered as a key sensor for mapping lakes [10], which are often too small for ocean color sensors largely used in water quality studies [e.g., 21]. Then, considering the capacity of revisiting the same area every 5 days (2–3 days toward mid to high latitudes because of the overlap of the paths), Sentinel-2 is also useful for tracking changes over time scales of weeks. Therefore, in the last years, a number of lake studies have been developed with Sentinel-2 [e.g., 29–34].

In our study, 45 Sentinel-2A and Sentinel-2B MSI images were chosen, 22 during the spring (end of March to end of May) and the remaining acquired between late August and the end of September (late summer). Images were selected based on clear sky conditions and low glint contamination. Level-2C standard products were downloaded via the Copernicus Open Access Hub. The level-2C standard product is atmospherically corrected using the Sen2Cor [35]. Although the level-2C products rely on an atmospheric correction scheme not specifically designed for retrieving water leaving reflectance, it was recently demonstrated that its accuracy was better for inland than for coastal waters [36]; moreover level-2C MSI data have been used both in lake [37] and shallow water [38] applications. The MSI bands 1–5 were resampled at 10 m and then converted into remote sensing reflectance (*Rrs*) by dividing level-2C reflectance by π. The remaining spectral bands were not used as chromaticity which is entirely determined by light in the visible part of the spectrum. Finally, imagery data in *Rrs* units were imported into a GIS environment for clipping to vector outlines of the lakes listed in the geodatabase of the Italian Institute for Environmental Protection and Research (ISPRA). The 10-m spatial resolution of Sentinel-2 allowed us to consider 170 lakes down to a minimum size of 0.3 km^2. For each lake, the *Rrs* values were extracted from a square area avoiding islands and shallow waters, thus reducing the chance for mixed land-water pixels and bottom effects. The area used corresponds to a pixel window ranging from 3-by-3 to 90-by-90 and from smaller to larger lakes.

The chromaticity coordinates x, y, and z from MSI-derived *Rrs* data were computed by normalizing the individual tristimulus values X, Y, and Z:

$$x = \frac{X}{X+Y+Z};\ y = \frac{Y}{X+Y+Z};\ z = \frac{Z}{X+Y+Z};\ \text{with}\ x + y + z = 1 \tag{1}$$

X, Y, and Z were computed as a linear weighted sum of MSI's five *Rrs* bands in the visible part of the spectrum (cf. **Table 1**) according to [24] (Eqs. (2)-(5)):

$$X = 8.356\, Rrs(b1) + 12.040\, Rrs(b2) + 53.696 Rrs(b3) + 32.087 Rrs(b4) + 0.487 Rrs(b5) \tag{2}$$

$$Y = 0.993\, Rrs(b1) + 23.122\, Rrs(b2) + 65.702 Rrs(b3) + 16.830 Rrs(b4) + 0.177 Rrs(b5) \tag{3}$$

$$Z = 43.487\, Rrs(b1) + 61.055\, Rrs(b2) + 1.778 Rrs(b3) + 0.015 Rrs(b4) \tag{4}$$

The x and y pairs were then plotted in the typical horseshoe-shaped chromaticity diagram (locus), where the center of the chromaticity diagram is the "white point" at which $x = y = z = 1/3$.

Any pair of x and y coordinates was then converted to hue angle (α). This is the angle between the line drawn from the white point to the x, y coordinate and the x-axis in anticlockwise direction. α was computed by using the four-quadrant arctangent function atan2 in MATLAB according to [22] (Eq. (5)):

$$\alpha = arctan\left(y - 1/3, x - 1/3\right) modulus 2\pi \tag{5}$$

The final step was the computation of dominant wavelength (λ_d). λ_d is the wavelength marked along the locus, and it is found as the intersection of the line drawn from the white point through the x, y coordinates.

3. Results and discussion

For each lake, x and y are plotted in the chromaticity diagram, commonly used to illustrate the color space and the range of colors in the sample. **Figure 1** depicts the natural color of our 170 lakes for each acquisition period in 2017. In spring, the colors of lakes are aligned elongated to a region spanning from blue toward green-orange; in late summer, the extent of the point cloud is greater and extends further into orange-red.

The optical properties of clean water are dominated by absorption and scattering by water molecules whose spectral dependence produces a blue reflectance spectrum. Therefore, the common perception that blue is "clean" is often true, while moving toward green, yellow, orange, and red, the optical effects of the other water components, such as phytoplankton, CDOM, and non-algal particle, become predominant. However, a simple back calculation from color to the direct causes of color change, e.g., proliferating phytoplankton or increasing sediment resuspension, is not possible. Nevertheless, any changes from blue can be reasonably attributed to decreasing water purity and is often also associated with a reduction in water clarity.

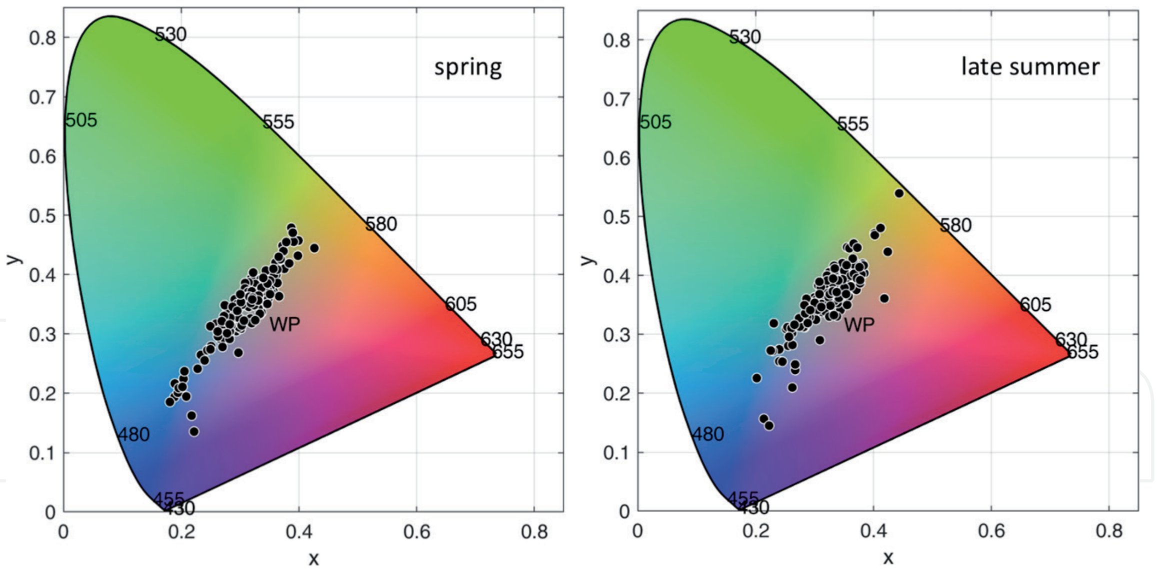

Figure 1.
Chromaticity diagram showing the color of water of 170 lake observations determined from Sentinel-2A/Sentinel-2B MSI data of 2017. Data related to spring are shown on the left, whereas those observed in late summer are shown on the right. The white point (WP: x = y = 1/3) is indicated as reference.

The frequency distribution of the dominant wavelength for the 170 lakes for both periods is plotted in **Figure 2**. Both histograms show a bimodal frequency distribution. In spring, most observations are in the blue-green part of the spectrum, with a secondary mode at green-yellow wavelengths. Vice versa, in late summer, most observations are in the green-yellow part of the spectrum and the secondary mode in the blue-green. To explain these changes, the lakes have been clustered according to three λ_d classes, defined as follows: blue (λ_d < 495 nm), green (495 nm < λ_d < 560 nm), and yellow (λ_d > 560 nm). In spring, 43% of lakes were classified as blue, 35% as green, and the last 22% as yellow. Moving toward late summer, most of the lakes were green (42%), then yellow (33%), and the remaining 25% as blue.

Of the 170 lakes, 96 did not show any transition from one color class to another, while 13 lakes moved from blue to yellow, showing a major change of optical properties also likely associated with a reduction in water clarity. The remaining 61 lakes showed smaller transitions to the neighboring color: 45 from blue to green or from green to yellow. The other 16 lakes showed transitions in the opposite direction, from green to blue or from yellow to green, suggesting improving water clarity from spring to late summer.

The geographic distribution of the three color classes is presented in **Figure 3**. Subalpine lakes in the northern part of the country including the largest lakes of the country (lakes Garda and Maggiore of 370 and 210 km^2, respectively) are distinctly blue in the spring. This lake district represents more than 80% of the total Italian lacustrine volume and is therefore of great interest. Moving from spring to late summer, a change of color toward green and yellow was observed in many of these lakes. Notably, the largest of these lakes, e.g., Lake Garda, remained blue.

A similar change is occurring in Sardinia, the second largest island of the country. Blue lakes turn yellow and green from spring to late summer. In contrast, only few lakes in Sicily show color transitions, and green and yellow colors prevail. Along the peninsula, more lakes are also blue during the spring than in late summer. However, a geographic gradient is seen in that summertime greening or yellowing is more common in the southern half of the peninsula.

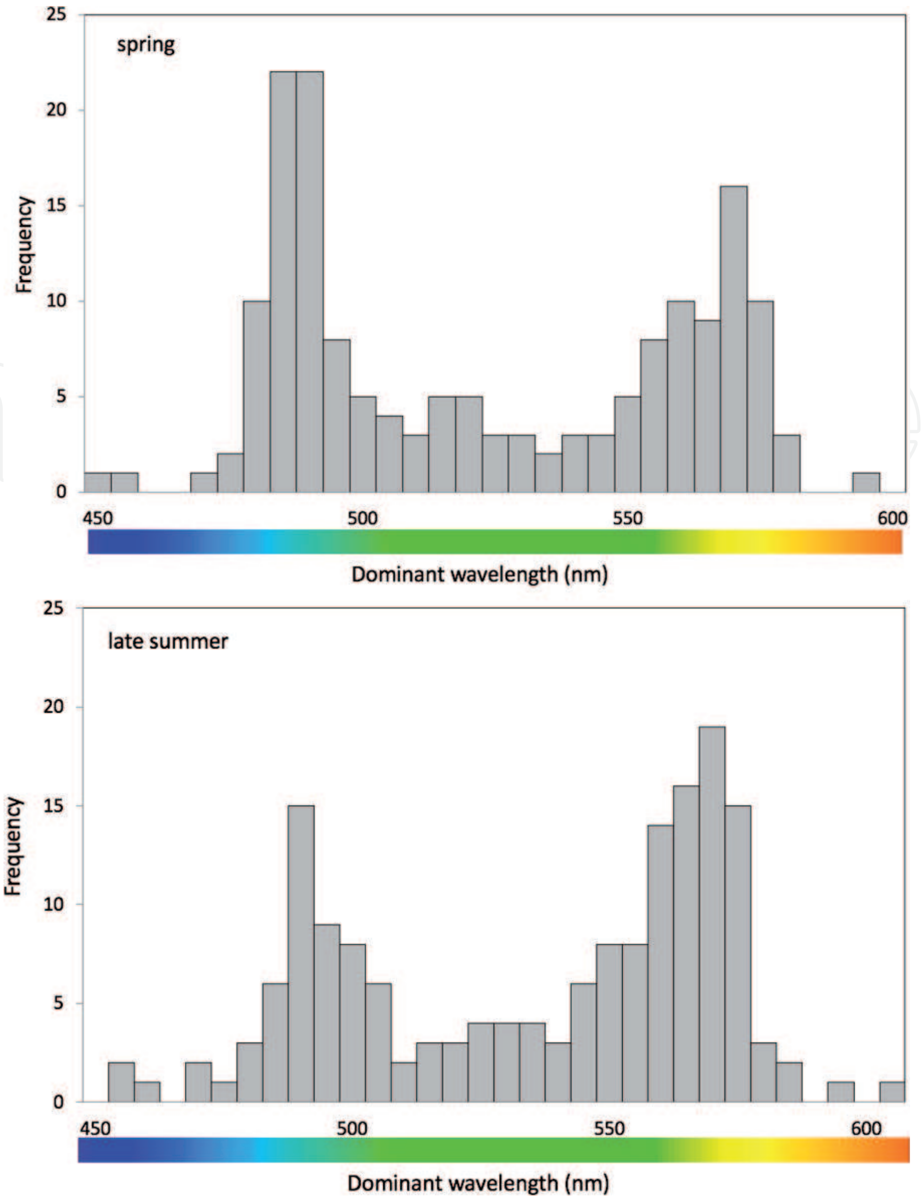

Figure 2.
Frequency histogram of dominant wavelength for the 170 lakes: on top, spring data; on bottom, late summer data.

To investigate these trends further, the lakes were split into four clusters according to latitude: northern (with latitudes >44°N), central (with latitudes in the range 44–41°N), southern lakes (with latitudes <44°N), and separately the lakes of Sardinia (**Figure 4**). Similar to general trends observed at the national scale, a progressive increase in λ_d was recorded moving from north to south in both the seasons. This is not surprising as the wide latitudinal range of Italy (~38–47°N) encompasses marked climatic, geological, topographic, and land use gradients.

A possible explanation, regardless of physical and chemical differences between lakes, is that the Mediterranean lakes are characterized by an advance of the growing season compared to northern ones. This may translate into an early start of the algal growth with significant effects on the color of the water. Consequently, it is quite natural to guess higher levels of productivity (colors basically more green-yellow) for southern lakes, as described by [39] at a global scale. Additionally, the differences between the two main Mediterranean and Italian islands, Sicily and Sardinia, are probably due to the geological and climatic differences between the two islands [40] and are likely exacerbated by the fact that their lakes are largely artificial reservoirs with site-specific trophic drivers.

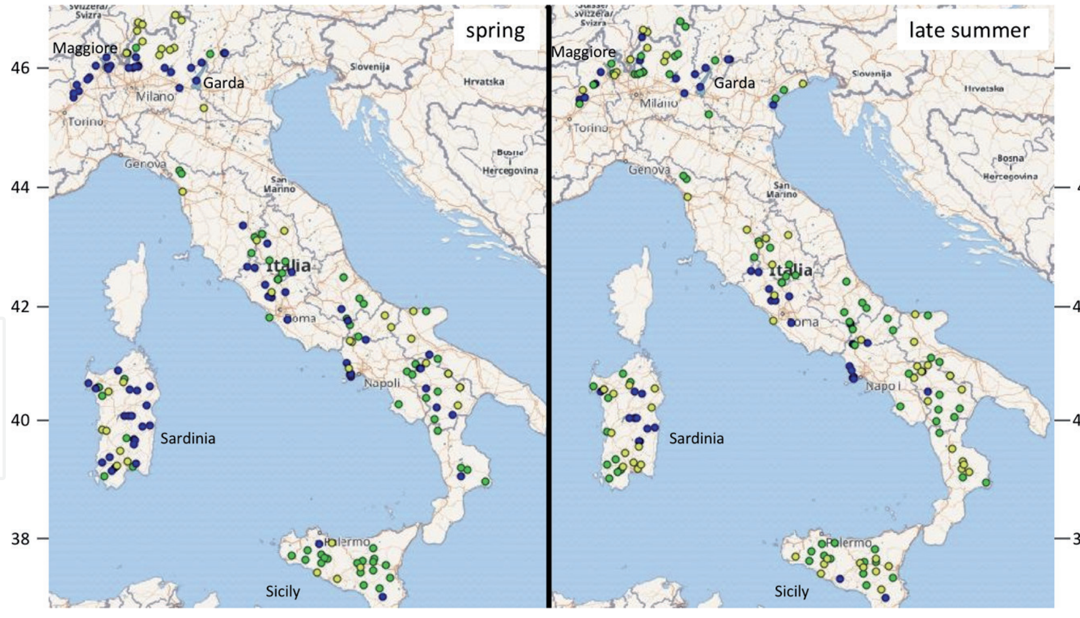

Figure 3.
Geographic distribution of lakes, colored according to their dominant wavelength: on left, spring observations; on right, summer observations. The latitudes in degrees are indicated as reference.

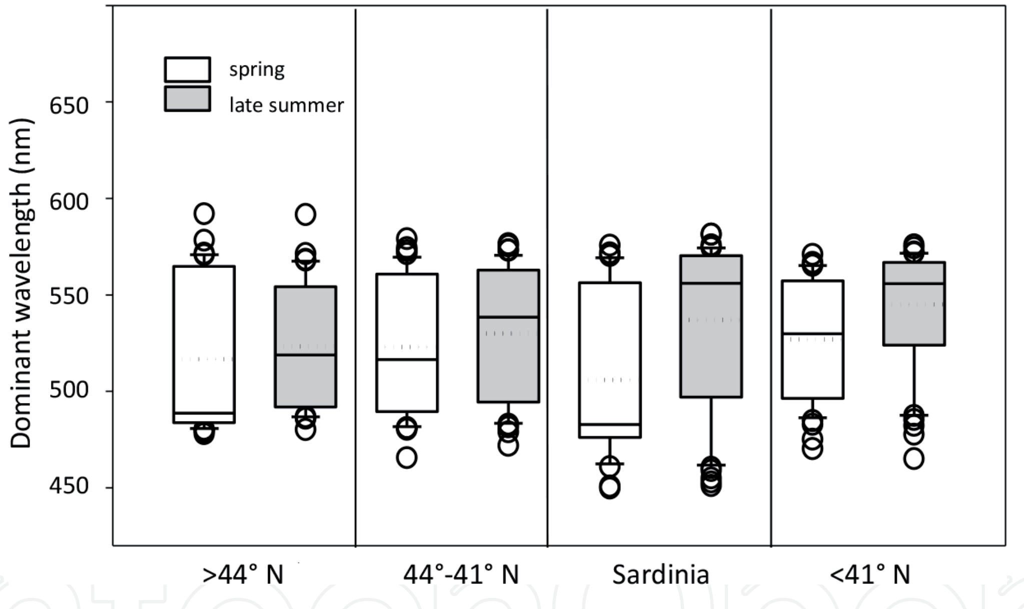

Figure 4.
Box plot depicting dominant wavelengths for spring (white) and autumn (gray) periods for northern (>44°N), central (44–41°N), Sardinian, and southern (<41°N) lakes.

4. Conclusion

In this study, the color of water, a simple and straightforward water quality attribute quantitatively described in terms of dominant wavelength, was retrieved from Sentinel-2A and Sentinel-2B MSI data. The method allowed us to map the color of 170 Italian lakes in two periods during 2017.

The results revealed a general increase in λ_d moving from north to south (in the range ~38–47°N) and from spring to late summer. This could be put in relation to the macroclimatic differences associated with the latitudinal gradient under investigation. Moreover, the observed trends suggest that the investigation of drivers of water chromaticity can contribute to fundamental understanding of lake water quality. This represents an opportunity for water managers who have to act under the dramatic effects of climate change on water availability and quality.

Our work shows that color observations are an efficient means to capture an intuitive water quality attribute at spatial and temporal scales practically impossible to achieve using ground-based observations. Further investigations are required to relate color of water to trophic status and traditional water quality metrics such as chlorophyll *a* concentration and suspended particulate matter. Such relationships most likely require the classification of lakes into bio-optical types [14, 16] which can also be assisted by remote sensing observations. Such knowledge would help to better understand and disentangle the main determinants of lake productivity such as the role of physical, chemical, and morphometric traits that are generally acknowledged as pivotal drivers of primary production [26].

For more than four decades, satellite sensors have been used for lake monitoring, and since 2015, Sentinel-2 MSI provides free and open data at a spatial resolution suitable for small- to medium-sized lakes (down to 0.3 km^2). MSI has similar spectral and spatial resolution as the Landsat series of satellites which allows the new data to be analyzed in continuity with historical imagery spanning back four decades. The color of water as calculated in this work is a promising water quality attribute for time series analysis as it does not rely on algorithms depending on inherent optical properties that have to be calibrated with field observations. While the present study only looked at two seasons in the same year, a long-term analysis could investigate the timing of summertime greening of the lakes in response to climatic forcing mechanism.

Ongoing research is focused on extending the color mapping over past observations. Future applications of chromaticity analysis are promising as each Sentinel-2 satellite has a 7-year lifetime design, and they are planned to be replaced in the framework of ESA's Copernicus Program in 2022–2023 by new identical missions. This ensures continuity of the data record to 2030 and provides the opportunity for lake water quality monitoring for decades from now.

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Conflict of interest

No potential conflict of interest is reported by the authors.

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