Remote Sensing of Environment 136 (2013) 433–441

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Spatial and temporal evolution of the St. Lawrence River spectral profile: A 25-year case study using Landsat 5 and 7 imagery

Philippe Massicotte *, Denis Gratton, Jean-Jacques Frenette, Ali A. Assani

Département des Sciences de L'environnement, Université du Québec à Trois-Rivières, Trois-Rivières, Canada
Centre de Recherche sur les Interactions Bassins Versants - Écosystèmes Aquatiques (RIVE), Canada

A R T I C L E I N F O

Article history:
Received 15 February 2013
Received in revised form 6 May 2013
Accepted 11 May 2013
Available online 22 June 2013

Keywords:
Landsat
Color producing agent (CPA)
Large river
Riverscape
Water color
SPIM
CDOM
St. Lawrence River
Time-series

A B S T R A C T

Underwater light characteristics (quality and quantity) are important drivers of many ecological processes in aquatic systems. However, the mechanisms driving the underwater light climate in large rivers are poorly understood due to the complex interactions among color-producing agents (CPAs), which can vary in space and time. A compelling example of such a complex interaction among CPAs concerns the St. Lawrence River, where chromophoric dissolved organic matter and suspended inorganic particulate matter interact to structure the underwater spectral environment. Because such interactions can be complex, the combined net effect of CPAs on water color is not intuitive and remains to be evaluated. To resolve the spatial and temporal dynamics of the spectral profile in the St. Lawrence River, we analyzed a series of 44 Landsat 5 and 7 images, distributed between 1984 and 2009, which cover the main freshwater section of the river. Rather than following linear trends along the longitudinal axis, the spectral profiles on spectral bands (blue, green and red) presented three distinctive spatial patterns. We argue that matter injected by tributaries and discontinuous zones of the river strongly impacts water color by modulating the balance among CPAs. We also clearly demonstrate a marked trend between 1984 and 2009 toward decreasing reflectance values on bands 1, 2 and 3, presumably in response to changes in land use in the surrounding watershed.

1. Introduction

Underwater light characteristics (quality and quantity) are important drivers of many ecological processes, such as primary productivity of photosynthetic communities (Frenette et al., 2012; Kirk, 1994). Underwater light also determines freshwater productivity through its influence on the fatty-acid composition of seston and its nutritional quality for primary consumers (Pommier et al., 2012). Many factors influence the spectral pattern of underwater light in aquatic environments, and these can vary in time and space (Gallegos, 2005). However, the mechanisms driving the bio-optical properties in one system may differ fundamentally from those in another system. In marine systems, for instance, chlorophyll (chl *a*), as an indicator of phytoplankton development, is one of the main color-producing agents (CPAs) determining the optical properties of surface water (Victoriano & Javier, 2004). Conversely, in large river ecosystems, optical characteristics of inland brownish water are largely determined by the watershed (Frenette et al., 2003, 2012). In these systems, chl *a* is likely to make a relatively small contribution to the water color since terrestrial inputs of chromophoric dissolved organic matter (CDOM) (Biber et al., 2008; Christian & Sheng, 2003; Gallegos, 2005) and suspended inorganic particulate matter (SPIM) (Ma et al., 2006) contribute significantly more to the water color than Chl *a*. The influence of CPAs (i.e., their effects on water color) on large rivers has received little attention compared with oceans or coastal systems and remains to be evaluated (Julian et al., 2008).

Traditionally, field measurements were needed to characterize the optical profile of aquatic environments, and this constraint restricted the spatial and temporal scales of research. Such limitations on analyzing the long-term trends of spectral changes over a large area had many implications. First, they imposed limits on our capacity to have a clear, global representation of the light climate that prevails in these ecosystems (Julian et al., 2013). Second, long time-series data sets for water color were generally missing or incomplete, introducing serious bias to the conclusions that could be drawn (Charron et al., 2008). To overcome these shortcomings, remote sensing and analysis of satellite images have allowed coverage of larger areas with a spatial resolution fine enough (ex.: 30 m with Landsat imagery) to detect local changes (Bukata, 2005). Moreover, satellite imagery has provided information over a wide range of spectral bands, which can be combined to obtain a clear picture of specific optical properties of water from local to global scales. Therefore, with our understanding of the principal color-

* Corresponding author at: Université du Québec à Trois-Rivières (UQTR), Département des Sciences de L'environnement, Centre de Recherche sur les Interactions Bassins Versants-Écosystèmes Aquatiques (RIVE), Pavillon Léon-Provancher Local 3413, 3351, boul. des Forges CP 500, Trois-Rivières (QC) G9A 5H7, Canada. Tel.: +1 819 376 5011x3402; fax: +1 819 376 5084.
E-mail address: philippe.massicotte@uqtr.ca (P. Massicotte).

0034-4257/$ – see front matter. Crown Copyright © 2013 Published by Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.rse.2013.05.028

producing agents of water, spectral images can be used to follow the evolution of water color over greater spatial and temporal scales.

Despite certain local and site-specific studies (Shafique et al., 2003), the use of satellite imagery on inland water has received limited attention compared to oceans (Morel, 1980; Morel & Prieur, 1977; Werdell & Bailey, 2005) and coastal environments (Lahet et al., 2001). Consequently, studies in large river ecosystems are usually limited in their spatial and temporal scales, and they do not address the question of temporal variation over enough time to detect regional or global trends (Julian et al., 2013). Moreover, long-term spectral monitoring on large rivers, and on inland water in general (Bukata, 2005), has been sparse in recent decades, leading to the current lack of time-series data sets. Additionally, most of these studies usually deal with one CPA at a time and limit the analysis of interaction (i.e., the balance) between the CDOM and SPIM components, where CDOM is marked by absorbance mainly on band 1 (blue) but also band 2 (green) on the Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) instruments, and SPIM is marked by reflectance in the red spectral domain: band 3 on Landsat TM and ETM instruments. Because such interactions can be complex, the combined net effect of CPAs on water color in large rivers is not intuitive, and the accuracy of measuring inland water color to assess water quality remains to be evaluated. Such an evaluation presents a considerable challenge (Bukata, 2005).

A compelling example of one such complex interaction among CPAs concerns the St. Lawrence River (SLR). As a consequence of the SLR's numerous tributaries and the surrounding terrestrial environment, CDOM and SPIM strongly interact and constitute important agents contributing to the underwater color (Frenette et al., 2003, 2006, 2012). Because CDOM quality (i.e., composition) reflects the dynamic interplay among sources and biogeochemical reactions, the hydrologic regime, land cover and corresponding management practices can have a significant impact on CDOM biogeochemistry (Jaffe et al., 2008). Thus, the balance between CPAs (CDOM and SPIM in this study) contributes to the creation of reaches with contrasting bio-optical signatures that are likely to vary in time and space.

For these reasons, there is a need for fundamental information regarding how heterogeneous watersheds influence the spatial and temporal spectral profiles of large rivers (Julian et al., 2013, 2008). With this in mind, the aims of this study are to: (1) determine the spatial pattern and variation of water color in the SLR, (2) determine the general trend of such changes over the past 25 years, and (3) highlight the principal CPAs underlying the observed spatial and temporal changes.

To resolve the spatial and temporal dynamic of the spectral profile in the SLR, we analyzed a series of 44 Landsat 5 and 7 images distributed between 1984 and 2009. We hypothesize that rather than following linear trends, the water color of large rivers will exhibit longitudinal discontinuities that will occur mostly near major tributaries because of inputs of colored matter (CDOM and SPIM). Moreover, we speculate that these discontinuities will vary over time as a consequence of land-use change in the surrounding watersheds and management policies that determine the type and quantity of matter injected into the river.

2. Material and methods

2.1. Study site and data set

The St. Lawrence River (SLR) is a large river system, integrating a wide variety of landscapes (Fig. 1). It is the second-largest river (in terms of discharge) in North America (Allan & Castillo, 2007) and globally ranks 19th and 20th, respectively, in terms of drainage area and average discharge rate. The SLR forms a complex system composed of a mosaic of heterogeneous zones such as fluvial lakes, connecting reaches and wetlands, interacting with inflowing tributaries to produce a strong longitudinal and lateral connectivity between aquatic and terrestrial environments (Frenette et al., 2012). It is characterized by physical continuities and discontinuities that operate at various spatial scales along both the longitudinal and lateral axes. Terrestrial-aquatic exchanges between the tributaries and the landscape, superimposed over the hydrology, bathymetry, climate and drainage network (Assani et al., 2010; Benda et al., 2004b), exert a significant impact on the physical characteristics of the receiving river (Frenette et al., 2003; Turner, 1989).

The SLR and its tributaries drain a watershed of 1,600,000 km^2, where land use is dominated by urbanization near Montreal and areas of agriculture, pasture, forests and wetlands in the mid and lower reaches of the river system (Frenette et al., 2006; Vis et al., 2007). For instance, water intrusions from tributaries become distinct water masses flowing down the river and contribute to spatial and temporal heterogeneity in optical characteristics and transport times (Frenette et al., 2003, 2006; Rice et al., 2006). Additionally, the hydrodynamic regime of the SLR imposes a directional connectivity between and within habitats, which shapes the spatial distribution of CDOM (Massicotte & Frenette, 2011). The data set used in this study consisted of 44 Landsat 5 and 7 TM and ETM images (6610 × 6000 pixels at a resolution of 30 × 30 m; row 14, path 28; see Fig. 2) taken between 1984 and 2009 (http://earthexplorer.usgs.gov). Images were selected from ice-free periods when the atmosphere was clear (cloud cover < 5%).

2.2. Radiometric correction and atmospheric effect attenuation

Prior to analysis, radiometric calibrations were applied to convert 8-bit satellite-quantized calibrated digital numbers to at-satellite top-of-atmosphere reflectance 32-bit values (Canty et al., 2004; Chander et al., 2009; Schroeder et al., 2006). All images (Landsat 5 and Landsat 7) were also corrected for sensor degradation using the most current radiometric calibration coefficients (Chander et al., 2009).

Before analyzing a time series of images, applying a procedure to attenuate atmospheric effect can standardize any atmosphere-related changes in top-of-atmosphere reflectance for the image set. We did this using a set of pseudo-invariant features ($n = 257$) that were evenly distributed over the study area. We selected these features by identifying pixels on the landscape that presented the lowest variance over the 25-year period. Visual examination determined that most of the pseudo-invariant features were in urban areas, mostly on anthropogenic structures such as airports and buildings, but in some cases were in mature forest cover. We used regression coefficients between a reference image (2009/09/02, cloud cover 0%) and all other images to normalize images for atmospheric effects (Mahiny & Turner, 2007; Schott et al., 1988). The linear regressions between the reference and target images (those to be corrected) presented, on average, high coefficients of determination (band 1, mean-$R^2 = 0.957$; band 2, mean-$R^2 = 0.978$; band 3, mean-$R^2 = 0.985$). Histogram of reflectance values of the PIFs located on the reference image showed normal-distribution on the three bands (image not shown). Moreover, the high dynamic range in reflectance (0.087–0.171 on band 1, 0.075–0.197 on band 2 and 0.060–0.223 on band 3) ensured the reliability of the correction procedure. It is to be noted that the atmospheric corrections procedure did not produce negative reflectance values. Radiometric and atmospheric corrections were performed in MATLAB 2010a.

2.3. Data extraction and methodological framework

To track the color change that occurred in the central water mass along a longitudinal axis of the deepest part of the SLR, we used a vector from the Quebec Ministry of Natural Resources that goes through the maritime channel (Figs. 1 and 2). This water mass integrates, by lateral mixing, many optical and water-mass changes that occur in the near-shore areas. This corridor represents the area in the SLR with a maximum depth (≥1.3 m) and thus avoids upwelling radiometric contributions from the river bed that could occur in shallower