Evaluation of Earth Observation Systems for Estimating Environmental Determinants of Microbial Contamination in Recreational Waters

Serge Olivier Kotchi, Stéphanie Brazeau, Patricia Turgeon, Yann Pelcat, Julie Légaré, Martin-Pierre Lavigne, Francine Nzang Essono, Richard A. Fournier, and Pascal Michel

***Abstract*—Public health risks related to the microbial contamination of recreational waters are increased by global environmental change. Intensification of agriculture, urban sprawl, and climate change are some of the changes which can lead to favorable conditions for the emergence of waterborne diseases. Earth observation (EO) images have several advantages for the characterization and monitoring of environmental determinants that could be associated with the risk of microbial contamination of recreational waters in vast territories like Canada. There are a large number of EO systems characterized by different spatial, temporal, spectral, and radiometric resolutions. Also, they have different levels of accessibility. In this study, we compared several EO systems for the estimation of environmental determinants to assess their usefulness and their added value in monitoring programs of recreational waters. Satellite images from EO systems WorldView-2, GeoEye-1, SPOT-5/HRG, Landsat-5/TM, Envisat/MERIS, Terra/MODIS, NOAA/AVHRR, and Radarsat-2 were acquired in 2010 and 2011 in southern Quebec, Canada. A supervised classification of these images with a maximum likelihood algorithm was used to estimate five key environmental determinants (agricultural land, impervious surfaces, water, forest, and wetlands) within the area of influence of 78 beaches. Logistic regression models were developed to establish the relationship between fecal contamination of beaches and environmental determinants derived from satellite images. The power prediction of these models and criteria such as accuracy of classified images, the ability of the sensor to detect environmental determinants in the area of influence of beaches, the correlation between the estimated environmental determinants in the area of influence by the sensor with those estimated by very high spatial resolution reference sensors (WorldView-2 and GeoEye-1), and general criteria of accessibility (cost of the images, imaging swath, satellite revisit interval, hours of work, and expertise and material required to process the images) were used to evaluate the EO systems. The logistic regression model establishing the relationship between environmental determinants from Landsat-5/TM images and the level of fecal contamination of beaches is the one which performs best. These images are also those that best meet all of the evaluation criteria. This study showed that environmental determinants like agricultural lands and impervious surfaces present in the area of influence of beaches are those which contribute the most to the microbial contamination of beaches. Our study demonstrated the utility and the added value that EO images could bring to programs monitoring the microbial contamination of recreational waters.**

***Index Terms*—Environmental determinants, epidemiology, image classification, microbial contamination, optical imaging, radar imaging, remote sensing, water pollution.**

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I. Introduction

GLOBAL environmental change (climate change, population growth, urbanization, and intensification of agricultural production) has given rise to the emergence and re-emergence of many waterborne diseases (*Campylobacter, Cryptosporidium, Escherichia coli O157: H7, Vibrio cholerae O139*, etc.) [1]–[12]. These diseases are the most significant causes of mortality worldwide [13], [14]. Monitoring programs involve sampling recreational water bodies to produce laboratory estimates of microbial contamination [4], [15]–[17]. However, the number of water bodies to monitor and laboratory delays in estimating microbial indicators are obstacles to the evaluation and monitoring of public health risks over large areas like Canada, which has many remote and isolated bodies of water. Several authors highlight the importance of developing new methods to help detect microbial contamination of recreational waters in a timely manner to better prevent public health risks [7], [11], [16], [18], [19]. Environmental conditions around water bodies are important factors in the risk of microbial contamination [20]–[23]. The description and monitoring of these conditions can help target recreational waters most at risk to optimize resources of monitoring programs and reduce population exposure to potentially contaminated water [24].

Earth observation (EO) systems provide a framework for the assessment and monitoring of these determinants over large areas [6], [7], [16], [17], [25]–[27]. However, there are a multitude of EO systems, characterized by types of sensors which differ in spatial, spectral, radiometric, and temporal resolutions as well as levels of accessibility. This leads to different capabilities of detecting and monitoring environmental determinants. A comparative evaluation of EO systems was conducted in this study to identify those which enable better assessment and monitoring of environmental determinants of microbial

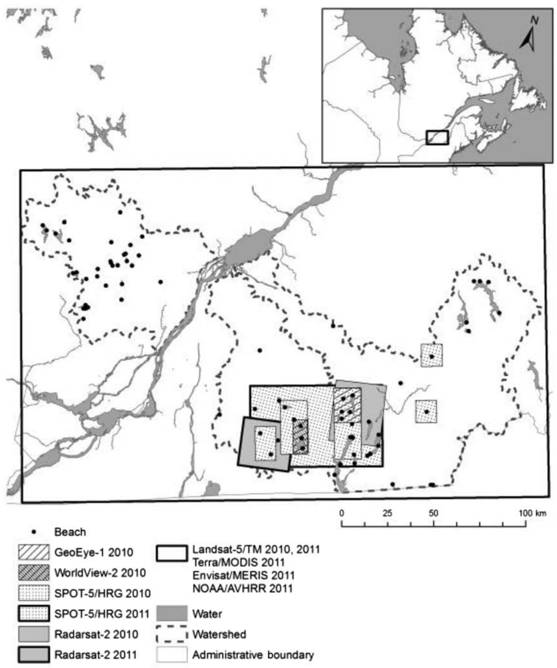

Fig. 1. Study area, beaches, and coverage of satellite images used in the study.

contamination risk in the proximal zones of recreational water bodies. As such, the objective of this study is the evaluation of EO systems in the context of estimating the environmental determinants of the risk of microbial contamination of recreational waters. This project is part of a research initiative on recreational waters conducted by the Public Health Agency of Canada [7], [25].

II. Methods

A. Study Area

The studied beaches were located on lakes and in three watersheds (watersheds of rivers *L'Assomption*, *Yamaska,* and *Saint-François*) in southern Québec, Canada (Fig. 1). The number of beaches studied across these basins varied between 22 and 78 according to the coverage of satellite images.

B. Microbial Contamination Measures

Measurements of fecal coliform concentrations were made by the Programme Environnement-Plage, a recreational water quality monitoring program in the province of Quebec. According to this program, water samples were taken in June, July, and August every summer of the study period (2004–2011), with an average of three samples taken per summer. Also, in this program, beaches were classified according to their average fecal coliform concentration after each harvest: a group "A" (excellent quality) beach is classified as having a test result of 0–20 colony-forming unit (CFU)/100 ml. Similarly, a group "B" beach (good) has 21–100 CFU/100 ml, group "C" (poor) has 101–200 CFU/ml, and group "D" (polluted) has over 200 CFU/100 ml found in the sampled water. A more description of this program could be found at [52]. For this study, the geometric mean of fecal coliform concentrations of all samples taken during the study period was taken as an index to indicate the overall contamination level of each beach. Turgeon *et al.* [17] present a more detailed description of the sampling method.

C. Estimation of Environmental Determinants

Four key environmental determinants were retrieved from satellite images and used to assess their impact on the level of fecal contamination of beaches: agricultural lands, forests, wetlands, and impervious surfaces, which were used as a proxy for urban areas. These land types are known to influence water quality either by being sources of contamination or by acting as protective areas around beaches [16]. Feedlots, irrigation, and fertilizer applications to agricultural lands are sources of pathogens. Drainage of these lands can result in a large amount of pathogens in surface water [53]. Runoff waters from impervious surfaces (residential, commercial, and industrial areas) can carry bacteria, dissolved solids, and a large amount of sediment and nutrients [53]. Contaminants present in those waters can be transported more easily by impervious surfaces to the lakes [54]. Forests can reduce soil erosion and act as a filter during runoff events. This action can limit the transport of sediments and microorganisms into surface waters. Wetlands play a buffer role for retaining sediments and populations of pathogens that can contaminate water bodies. Their location in the territory becomes an important factor of the reduction in microbial contamination of water bodies [55]. However, wetlands near pastoral streams may be an important source of fecal contamination, especially during major rain events, resulting in a flow of wetlands to water bodies [56]. The proximity of the river system to the sources of fecal contamination such as farms and crop areas is also an important risk factor for microbial contamination of surface waters [57]. Four additional determinants associated with specific characteristics of the beaches and not extracted from satellite imagery were also added to the analysis: land topography, number of tributaries, the lake area, and the plant hardiness zone (PHZ) calculated by Natural Resources Canada [28]. PHZ is an index of suitability for growth of trees, shrubs, and flowers, and was used as an average climatic condition of a region.

Values associated with these determinants were calculated for each beach according to a hydrological area naturally drained into the lake (area of influence). The area of influence of the beaches contributes most to microbial contamination. This area was defined as the intersection of the lake's watershed and a 2-km radius from the beach and description of the method used to define these areas can be found in the publication of [23].

The estimation of environmental determinants was performed by the classification of EO images. Field observations and reference data from various geodatabases were used for the processing of the images, their classification, and their accuracy assessment. Fig. 2 presents EO systems used and the workflow of data acquisition, processing, and analysis.

1) EO Systems Which Are Compared: The choice of EO systems was based on different characteristics related to the spatial resolution, spectral resolution, and temporal resolution (SST space), the type of sensor and the accessibility of the

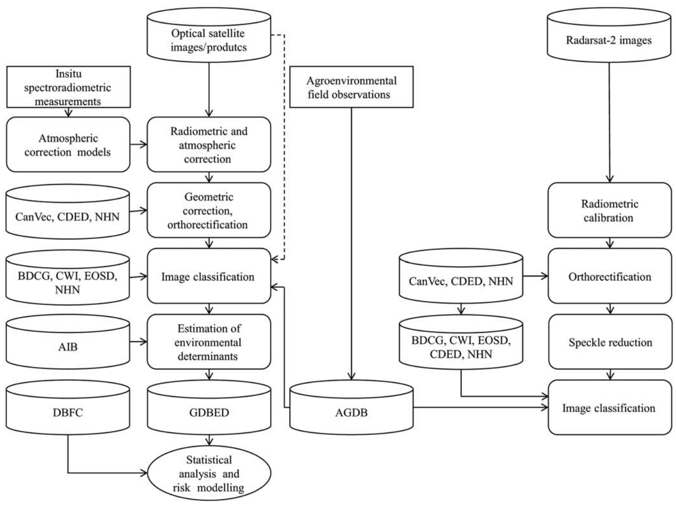

Fig. 2. Framework of remote sensing data acquisition, processing, and analysis. AGDB, agroenvironmental geodatabase; AIB, areas of influence of beaches; BDCG, *Base de données de cultures généralisées* (Agricultural census database of Quebec province); CDED, Canadian Digital Elevation Data; CWI, Canadian Wetland Inventory; DBFC, database of fecal contamination; EOSD, Earth Observation for Sustainable Development of Forests; GDBED, geodatabase of the proportion of environmental determinants in the areas of influence of beaches; and NHN, National Hydro Network.

images. We identified four classes of resolution (very high, high, medium, and low) in each dimension of the SST space (Table I). In the spatial dimension of the SST space, we have the following classes of resolution: very high spatial resolution ($\mathrm{VSR} \leq 5\ \mathrm{m}$), high spatial resolution ($5\ \mathrm{m} < \mathrm{HSR} \leq 30\ \mathrm{m}$), medium spatial resolution ($30\ \mathrm{m} < \mathrm{MSR} \leq 500\ \mathrm{m}$), and low spatial resolution ($\mathrm{LSR} > 500\ \mathrm{m}$). Very high spectral resolution ($\mathrm{VER} > 30\ \mathrm{bands}$), high spectral resolution ($5\ \mathrm{bands} < \mathrm{HER} \leq 30\ \mathrm{bands}$), medium spectral resolution ($3\ \mathrm{bands} < \mathrm{MER} \leq 5\ \mathrm{bands}$), and low spectral resolution ($\mathrm{LER} \leq 3\ \mathrm{bands}$) are the classes of the spectral dimension of the SST space. The temporal dimension of this space was defined by the following classes: very high temporal resolution ($\mathrm{VTR} \leq 1\ \mathrm{day}$), high temporal resolution ($1\ \mathrm{day} < \mathrm{HTR} \leq 3\ \mathrm{days}$), medium temporal resolution ($3\ \mathrm{days} < \mathrm{MTR} \leq 16\ \mathrm{days}$), and low temporal resolution ($\mathrm{LTR} \geq 16\ \mathrm{days}$). This characterization allowed us to choose and evaluate the following systems: WorldView-2 (VSR, HER, MTR), GeoEye-1 (VSR, MER, MTR), SPOT-5/HRG (HSR, MER, HTR), Landsat-5/TM (HSR, HER, LTR), Envisat/MERIS (MSR, HER, MTR), Terra, Aqua/MODIS (MSR, VER, HTR), and NOAA/AVHRR (LSR, MER, VTR). These are optical sensors. Images from active sensor RADARSAT-2 Fine Quad-Polarization Beam mode (VSR, MER, VTR) were also assessed. According to the criterion of accessibility, data from commercial sensors (WorldView-2, GeoEye-1, SPOT-5/HRG), governmental access data (RADARSAT-2), and free access data (Landsat-5/TM, Envisat/MERIS, Terra, Aqua/MODIS and NOAA/AVHRR) were evaluated. Table II presents the resolutions of these EO systems.

2) Satellite Images Used: Satellite images were acquired between May and September of the years 2010 and 2011 (Table III). Full coverage of the study area (territory of the three watersheds) was obtained through the use of free access images. Images from commercial sensors and Radarsat-2 were acquired for subsets of the full study area (Fig. 1).

3) Ground Truth Data: Spectroradiometric measurements and ground truth observations were performed for image correction and classification. Spectroradiometric measurements were carried out on water and other surfaces types (sand, asphalt, and grass) in the beach areas. Ground truth observations focused on the identification and description of the agricultural land in the periods of the acquisition of satellite images. The observation sites were generated randomly in the entire area using the function “create random points” in ArcGIS 10.0 (ESRI, Redlands, CA). Agricultural census data and road data were used to limit the selection of ground truth sites to farms which are near a road. All of the *in situ* observations were made in the area covered by the SPOT-5 images (Fig. 1). Ground truth data were used to establish an agroenvironmental geodatabase (AGDB) (Fig. 2).

4) Satellite Image Processing: The processing of satellite images included radiometric, atmospheric, and geometric corrections to better compare the images acquired at different dates and with different EO systems, and also to improve the results of image classification algorithms. Spectroradiometric measurements were used to perform the atmospheric correction of images from GeoEye-1, WorldView-2, SPOT-5, and Landsat-5 according to the empirical line method [29]–[31]. The products we used for MODIS (MOD09GA) and MERIS (MER_FRS_2P) are surface reflectance data and therefore did not need to be atmospherically corrected. AVHRR images were calibrated to reflectance and surface temperature using the procedure ENVI_AVHRR_CALIBRATE_DOIT (Exelis Visual Information Solutions, Boulder, CO). Geometric correction of those images was computed with the procedure ENVI_AVHRR_WARP_DOIT of the same software. Images from optical sensors are georeferenced products. The processing of Radarsat-2 images focused on radiometric calibration, application of a speckle filter and orthorectification (Fig. 2). A gamma filter of 5×5 pixels was used. The orthorectification was performed using Toutin’s three-dimensional (3-D) physical model [32], implemented in OrthoEngine, Geomatica 10.3 (PCI Geomatics, Richmond Hill, ON). A total of 9–15 control points were collected per image. Road data from CanVec [33] and elevation data from the Canadian Digital Elevation Data (CDED) [34] were used as planimetric and altimetric references, respectively. A fusion of SPOT-5 multispectral and panchromatic images was performed for a high spatial resolution (5 m) multisensor classification with Radarsat-2 images. The intensity-hue-saturation (IHS) transformation approach [58]–[60] was used to perform the fusion of SPOT-5 images. The “FUSE” function of Geomatica 10.3 software (PCI Geomatics, Richmond Hill, ON) was used to apply the IHS transformation. Spatial integration of SPOT-5 fused images and Radarsat-2 images was performed using an image-to-image coregistration [61].

5) Image Classification and Evaluation of the Estimation of Environmental Determinants in the Areas of Influence: The classification of satellite images was performed using a supervised classification approach based on the maximum

TABLE I
CLASSES OF RESOLUTIONS USED TO CATEGORIZE EARTH OBSERVATION SYSTEMS

Class of resolution	Dimension of the resolution space		
	Spatial (m)	Spectral	Temporal (days)
Very high	VSR : pixel ≤ 5	VER : NoB > 30	VTR : RT ≤ 1
High	HSR : 5 < pixel ≤ 30	HER : 5 < NoB ≤ 30	HTR : 1 < RT ≤ 3
Medium	MSR : 30 < pixel ≤ 500	MER : 3 < NoB ≤ 5	MTR : 3 < RT ≤ 16
Low	LSR : pixel > 500	LER : NoB ≤ 3	LTR : RT > 16

VSR, very high spatial resolution; HSR, high spatial resolution; MSR, medium spatial resolution; LSR, low spatial resolution; VER, very high spectral resolution; HER, high spectral resolution; MER, medium spectral resolution; LER, low spectral resolution; VTR, very high temporal resolution; HTR, high temporal resolution; MTR, medium temporal resolution; LTR, low temporal resolution; NoB, number of bands; RT, revisit time.

TABLE II
SPATIAL, SPECTRAL, AND TEMPORAL RESOLUTIONS OF EARTH OBSERVATION SYSTEMS USED

Satellite	Sensor	Spatial (m)	Spectral		Temporal (days)	
			NoB	Spectral bands (nm)	TR	RT
GeoEye-1	GeoEye-1	0.41 (PAN), 1.65 (MS)	5	B: 450 – 510; G: 510 – 580; R: 655 – 690; NIR: 780 – 920; PAN: 450 – 800	ND	RT ≤ 3
WorldView-2	WorldView-2	0.46 (PAN), 1.84 (MS)	8	NIR –1: 770 – 895; R: 630 – 690; G: 510 – 580; B: 450 – 510; RE: 705 – 745; Y: 585 – 625; C: 400 – 450; NIR–2: 860 – 1040; PAN: 450 – 800	ND	1.1 ≤ RT ≤ 3.7
SPOT-5	HRG	5 (PAN), 10 (MS), 20 (SWIR)	5	G: 500 – 590; R: 610 – 680; NIR: 780 – 890; SWIR: 1580 – 1750; PAN: 480 – 710	ND	2 ≤ RT ≤ 3
Landsat-5	TM	30 (MS), 120 (TIR)	7	B: 450 – 520; G: 520 – 600; R: 630 – 690; NIR: 760 – 900; SWIR–1: 1550 – 1750; TIR: 10400 – 12500; SWIR–2: 2080 – 2350	16	16
Terra	MODIS	250 (B_1 à B_2); 500 (B_3 à B_7); 1000 (B_8 à B_{36})	36	R: 620 –670; NIR: 841 –876; B: 459 –479; G: 545 –565; SWIR–1: 1230 –1250; SWIR–2: 1628 –1652; SWIR–3: 2105 –2155 (B_1 à B_7)	16	1 ≤ RT ≤ 2
Envisat	MERIS	300	15	G: 402.5 –422.5; I: 432.5 –452.5; B: 480 –500; C: 500 – 520; GY: 550 –570; O: 610 –630; R–1: 655 –675; R–2: 673.75 –688.75; R–3: 698.75 –718.75; NIR–1: 746.25 – 761.25; NIR–2: 756.875 –764.375; NIR–3: 763.75 –793.75; NIR–4: 845 –885; NIR–5: 875 –895; NIR–6: 890 –910	35	3
NOAA	AVHRR	1100	6	VIS: 580 –680; NIR: 725 –1100; SWIR: 1580 –1640; TIR–1: 3550 –3930; TIR–2: 10300 –11300; TIR–3: 11500 –12500	ND	0.5

NoB, number of spectral bands; TR, temporal resolution; RT, revisit time; ND, not defined; B, Blue; Bn, Band n; C, coastal; G, green; GY, green-yellow; I, indigo; MS, multispectral; NIR, near-infrared; O, orange; PAN, panchromatic; R, Red; RE, red edge; SWIR, shortwave infrared; TIR, thermal infrared; VIS, visible; Y, yellow; B_1 to B_{36}—Band 1 to Band 36.

TABLE III
DATE OF ACQUISITION AND SOURCE OF THE SATELLITE IMAGES

Sensor	Image identification	Date of acquisition	Image source
GeoEye-1	GEOEYE1_PO_U626360-2000443_PACGEO_464315	2010-08-19	Pacific Geomatics Limited (Surrey, BC, Canada)
WorldView-2	10JUL28154951-M2AS-052380336010_01_P001	2010-07-28	MDA Geospatial Services Inc. (Richmond, BC, Canada)
SPOT-5/HRG	56292591106161606491J 56262581106221551161J2 56272581107171610161J0 56272591107171610251J0	2010-06-16 2010-06-22 2011-07-17 2011-07-17	Iunctus Geomatics Corp. (Lethbridge, AB, Canada)
Landsat-5/TM	LT50150282011186 LT50140282011195 LT50140292011195 LT50130282011284 LT50130292011284	2010-07-05 2010-07-14 2010-07-14 2010-10-11 2010-10-11	http://glovis.usgs.gov
Terra/MODIS	MOD09GA.A2011198	2011-07-17	http://mrtweb.cr.usgs.gov
Envisat/MERIS	MER_FRS_1PNPDK20110714_151952_000005373104_00284_49005_1428	2011-07-20	http://earth.esa.int/resources/catalogues
NOAA/AVHRR	NSS.HRPT.NL.D11200.S1257.E1311.B5579393.WI	2011-07-19	http://www.class.ngdc.noaa.gov
RADARSAT-2	RS2_OK12793_PK139132_DK134255_FQ22_20100610_105312_HH_VV_HV_VH_SLC	2010-06-10	Canadian Space Agency (Saint-Hubert, QC, Canada)
	RS2_OK21426_PK226339_DK210978_FQ20_20110716_105734_HH_VV_HV_VH_SLC	2011-07-16	

TABLE IV
DIVERGENCE INDICES USED TO IMPROVE THE SEPARABILITY BETWEEN CLASSES

Index	Formulation
RDGI	$(\mathrm{SWIR}-\mathrm{R})/(2\times\mathrm{NIR})$
ADGI	$(\mathrm{G}+\mathrm{R}+\mathrm{MIR})/(\mathrm{m}\times(\mathrm{NIR}/\mathrm{SWIR}))$ $\mathrm{m} = 1000$
MDGI	$(\mathrm{G}-\mathrm{SWIR})\times(\mathrm{G}+\mathrm{SWIR})\times(\mathrm{SWIR}-\mathrm{NIR})$
TDGI	$(3(\mathrm{NIR}-\mathrm{R})/2)-((\mathrm{SWIR}-\mathrm{R})/2)-(\mathrm{NIR}-\mathrm{SWIR})$

RDGI, ratio divergence index; ADGI, additive divergence index; MDGI, multiplicative divergence index; TDGI, triangular divergence index; G, green; R, red; NIR, near-infrared; SWIR, shortwave infrared.

likelihood algorithm [35], [36]. This classification method is one of the most used [37]. The classification aimed to distinguish five main environmental determinants (agricultural land, surface water, forests, wetlands, and impervious surfaces). Bhattacharyya distance and Jeffries-Matusita distance [38], [39] were used to assess the spectral separability between classes. In addition to satellite image channels, vegetation indices, texture measures, and elevation data were used to improve the separability between classes. The last two variables were only used in the classification of Radarsat-2 images. Vegetation indices that were used included the normalized difference vegetation index (NDVI) [40], the global environmental monitoring index (GEMI) [41], the normalized difference water index (NDWI) [42], the specific leaf area vegetation index (SLAVI) [43], and the modified soil adjusted vegetation index (MSAVI2) [44]. New indices were also developed as part of this study to improve the separability between classes in the classification of optical images. These new indices are the ratio divergence index (RDGI), the additive divergence index (ADGI), the multiplicative divergence index (MDGI), and the triangular divergence index (TDGI). Table IV presents band equations related to those indices. Classification training site polygons were created for each satellite image. The training sites were created using reference geodatabases including AGDB, the Base de données de cultures généralisées (BDCG) [45], a census data of the province of Quebec, the Canadian Wetland Inventory (CWI) [46], the EO for Sustainable Development of Forests (EOSD) [47], the National Hydro Network (NHN) [48], CanVec [33], GoogleEarth (Google Inc., Mountain View, CA), and Google StreetView (Google Inc., Mountain View, CA). The classification of SPOT-5/Radarsat-2 multisensor image was also carried out using the above supervised classification based on maximum likelihood algorithm [35], [36]. Image bands used for this classification were SPOT-5 bands XS1, XS2, XS3, and XS4 derived from the fusion, the four polarimetric bands HH, HV, HV, and VV of Radarsat-2 image, as well as the sum and the product of these polarimetric bands, and finally one texture measure (entropy of band VH). Following the classification of satellite images, the proportion of surface occupied by each of the environmental determinants in the area of influence of the beaches was calculated. The calculation was achieved by dividing the sum of all surfaces of each determinant by the total surface of the area of influence.

The quantitative evaluation of EO systems regarding the estimation of environmental determinants was based on three criteria: the accuracy of classified images, the ability of the sensor to detect environmental determinants in the area of influence of beaches, and the correlation between the estimated environmental determinants in the area of influence by the sensor and those estimated by very high spatial resolution reference sensors (WorldView-2 and GeoEye-1). A good classification of satellite images related to the environmental determinants present in the study area is an essential condition for the use of these images in the monitoring of the microbial contamination risk that these determinants could represent. The quality of classified images was assessed with *in situ* data and reference geodatabases, using overall accuracy, Kappa coefficient, producer accuracy (PA), and user accuracy (UA) as error indicators [29], [49], [50]. The mean absolute difference between the proportion of surface occupied by environmental determinants estimated with the reference sensors images and those from other sensors was used to assess the ability of those sensors to estimate the right proportion of surface occupied by environmental determinants in the area of influence of beaches. Five areas of influence characterized by different proportions of environmental determinants were used for this assessment. The environmental determinants estimated using images from very high spatial resolution sensors represent the ground truth of land cover and land use with greater precision. Higher is the correlation between these environmental determinants and those estimated with the other sensors, and the greater is the ability of those sensors to represent this ground truth. This correlation was calculated using the Spearman correlation coefficient. The average correlation associated with each of the sensors was used to evaluate their performance.

D. Assessment of the Relationship Between Fecal Contamination and Environmental Determinants

Agricultural lands, forests, wetlands, and impervious surfaces are known to affect water quality (16). The relationship between these estimated environmental determinants using different EO systems and the level of microbial contamination of water bodies was assessed using logistic regression models. The objectives of this analysis was to model factors affecting beaches in the "nonexcellent" categories versus beaches in the excellent category (mean fecal coliform concentration of $<20\ \mathrm{CFU}/100\ \mathrm{mL}$) in accordance with the water quality program in place, and compare the sensor performances in statistical models. Hosmer–Lemeshow test was performed to assess the goodness-of-fit of the models with a significant ($p < 0.05$) value indicating a poor fit [51]. The capacity of the models to classify the beaches in the right category was evaluated by examining the receiver operating characteristic (ROC) curve and the percentage of concordant pairs [51]. All statistical procedures were performed using SAS software (SAS 9.2, SAS Institute Inc., NC, USA).

E. Evaluation of EO Systems' Accessibility

The evaluation of EO systems' accessibility was based on criteria such as cost of the images, imaging swath, satellite revisit interval, hours of work, and expertise and material required to process the images. Cost of satellite images is an important factor to be considered for their use in the assessment of microbial contamination risk in monitoring programs of recreational waters. This factor should be considered to ensure that the program remains sustainable. Imaging swath of satellite images is an important factor when they have to be used to cover large territories. The lesser the number of images to be used to cover the region of interest is, the lesser the time and effort needed for the assessment and monitoring of environmental determinants are. Satellite revisit time is an important factor to be taken account when cloud cover is common in the area and period of interest, as it could limit the accessibility to a cloud-free data on the study area. This is the case in southern Quebec in summer seasons. The higher the frequency of image acquisition is, the higher the probability to get valuable information on the study area is. We therefore considered the satellite revisit time to evaluate the performance of EO systems. The estimation of working hours includes all hours necessary for the acquisition, the processing and classification of images, and for the extraction of environmental determinants. For some sensors, products not requiring processing are already available. This reduces the time taken to integrate these data in the assessment of the risk of microbial contamination. The required expertise refers to knowledge and skills necessary for the processing and the classification of images. The required tools refer to software needed for these processing and these classifications.

For each evaluation criterion, the EO systems have been ordered according to their performance, and a score was assigned to them, ranking from 1 to 5; the best performing sensor received a score of 5. A global score was calculated for each system according to the ratio between the sum of the scores of all criteria and the sum of the maximum scores of these criteria.

III. Results and Discussions

A. *Classified Images and Precision of the Estimation of Environmental Determinants*

Classification of images with very high spatial resolution like WorldView-2 and GeoEye-1 resulted in a very good estimation of environmental determinants. All variables could be detected at a very fine scale. However, given the cost of these images and the geographic coverage of their scenes, they could not be used to estimate the environmental determinants across the full study area. The AVHRR image classified with a spatial resolution of 1100 m allows the identification of key environmental determinants occupying large geographic areas. However, some determinants present in more heterogeneous environments or covering smaller geographical areas cannot be detected. The MODIS classified image has a spatial resolution of 500 m. As in the case of the AVHRR image, environmental determinants occupying large geographical areas are clearly identified. Determinants such as lakes, rivers, and urban areas, however, are better detected here with the AVHRR images. As in the case of MODIS and AVHRR imagery, a single MERIS image provides a complete coverage of the study area, with a spatial resolution of 300 m. The classification of the image also allowed a good identification of environmental determinants

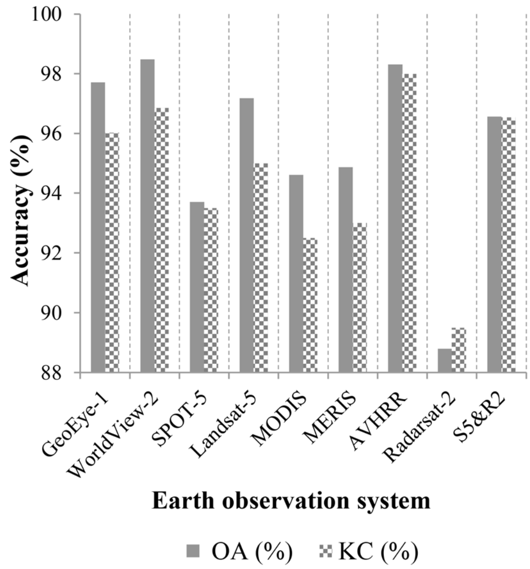

Fig. 3. Overall accuracy and kappa coefficient of classified images. S5&R2, multisensor image from SPOT-5 and Radarsat-2; OA, overall accuracy; and KC, Kappa coefficient.

occupying large geographic areas. The areas occupied by these determinants are better defined. Determinants such as wetlands could not be detected using the MERIS image classification as was the case of AVHRR and MODIS images. A full scene of Landsat-5 and portions of four other scenes were required to cover the study area. Processing and analysis of these images requires more investigation time than the first three sensors. Classified images from Landsat-5, with a spatial resolution of 30 m, allow better detection of areas occupied by environmental determinants in the study area. More heterogeneous environments and environmental determinants of smaller surfaces are better detected than with AVHRR, MODIS, and MERIS images. Environmental determinants were better identified with the classified SPOT-5 images, compared to classified Landsat-5, MERIS, MODIS, or AVHRR images. These images allowed a better classification of agricultural areas, as well as better detection of environmental determinants in more heterogeneous environments. However, the 20-m resolution SPOT-5 imagery footprint is very small and would have required 15 images to cover our study area which would have dramatically increased the time of processing and cost of the project. The classification of Radarsat-2 images demonstrated the ability to use these images for estimating environmental determinants such as agricultural lands, water surface, forest, wetlands, and impervious surfaces. Furthermore, these images offer the advantage of not being affected by clouds and other atmospheric conditions.

The accuracy of classifications by high spatial resolution images from WorldView-2 and GeoEye-1 is very high, with an overall accuracy of 98.48% and a Kappa coefficient of 0.97 (Fig. 3). This justifies the choice of these images for the evaluation of other sensors. Classification of satellite images for the estimation of environmental determinants in the study area produces very good results, with an overall accuracy of more than 88% and a kappa coefficient greater than

0.90 for all the evaluated sensors (Fig. 3). According to the PA and UA related to the estimation of each environmental determinant in the study area, the medium and low spatial resolution sensors MODIS ($92.35\% \leq$ PA $\leq 97.90\%$ and $83.89\% \leq$ UA $\leq 94.48\%$), MERIS ($93.83\% \leq$ PA $\leq 96.55\%$ and $86.64\% \leq$ UA $\leq 97.80\%$), and AVHRR ($97.39\% \leq$ PA $\leq 100\%$ and $92.91\% \leq$ UA $\leq 100\%$) allowed a very good estimate of the determinants, except for wetlands (Fig. 4). These features could not be classified using those medium and low spatial resolution sensors. The dimensions of their occurrences on the study area are usually much smaller than the spatial resolution of the sensors. Agricultural surfaces, water, forest, and impervious surfaces were also estimated in the study area with a very high accuracy by high spatial resolution sensors Landsat-5 ($93.33\% \leq$ PA $\leq 96.72\%$ and $71.93\% \leq$ UA $\leq 96.48\%$) and SPOT-5 ($89.16\% \leq$ PA $\leq 99.14\%$ and $81.83\% \leq$ UA $\leq 99.90\%$) (Fig. 4). Moreover, compared to the medium and low spatial resolution sensors, these sensors allowed the detection of wetlands (PA $= 95.56\%$, UA $= 64.53\%$ for Landsat-5 and PA $= 91.73\%$, UA $= 37.70\%$ for SPOT-5) (Fig. 4). Classified images from Landsat-5 and SPOT-5 achieved similar performance regarding precision indicators PA and UA, except for wetland, where Landsat-5 achieved significant higher UA value (Fig. 4). This similarity was also reported by Lu *et al.* [62] and Taylor *et al.* [63]. Compared to the other evaluated sensors, Radarsat-2 images allowed the estimation of each of the environmental determinants with less accuracy ($73.65\% \leq$ PA $\leq 96.55\%$ and $49.02\% \leq$ UA $\leq 98.82\%$) (Fig. 4). This less performance of Radar imagery was also highlighted by Schotten *et al.* [64]. Compared to the classified images of SPOT-5 and Radarsat-2, the classification of SPOT-5/Radarsat-2 multisensor image allowed a better detection and a better characterization of the spatial variability of environmental determinants. These determinants were classified with an overall accuracy of 96.56% and a Kappa coefficient of 96.54% (Fig. 3). Precision indicators related to each environmental determinants show that agricultural surfaces (PA $= 91.99\%$, UA $= 91.50\%$), impervious surfaces (PA $= 98.34\%$, UA $= 96.30\%$), forest (PA $= 99.05\%$, UA $= 99.18\%$), and water (PA $= 98.28\%$, UA $= 99.78\%$) were estimated with a very high accuracy (Fig. 4). And more specifically, there is a significant improvement in the estimation accuracy of wetlands (PA $= 100\%$; UA $= 60.59\%$) compared to the classification of SPOT-5 image and the classification of Radarsat-2 image (Fig. 4). Other authors reported higher accuracy of the classification of the fusion of multispectral and panchromatic images compared to multispectral images [62], [66].

The estimation accuracy of environmental determinants varies greatly in different classifications according to image acquisition date, sensors used, and thematic classes. The accuracy of the estimation with wetlands using SPOT-5/HRG and Landsat-5/TM images can vary by more than 60% depending on the date of image acquisition. For impervious surfaces, the same accuracy can vary more than 50% with Landsat-5/TM images. Images acquired in early spring or fall generally record better estimate environmental determinants in the study area.

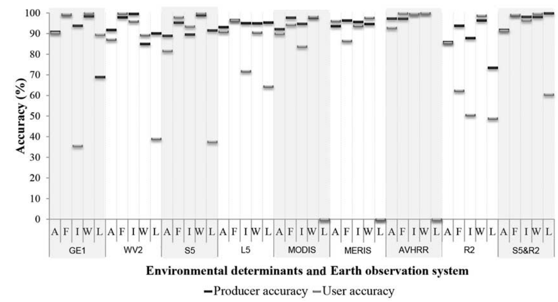

Fig. 4. Precision of the environmental determinant estimation according to satellite images used. A, agricultural land; F, forest; I, impervious surface; W, water; L, wetland; GE1, GeoEye-1; WV2, WorldView-2; S5, SPOT-5; L5, Landsat-5; R2, Radarsat-2; and S5&R2, multisensor image from SPOT-5 and Radarsat-2.

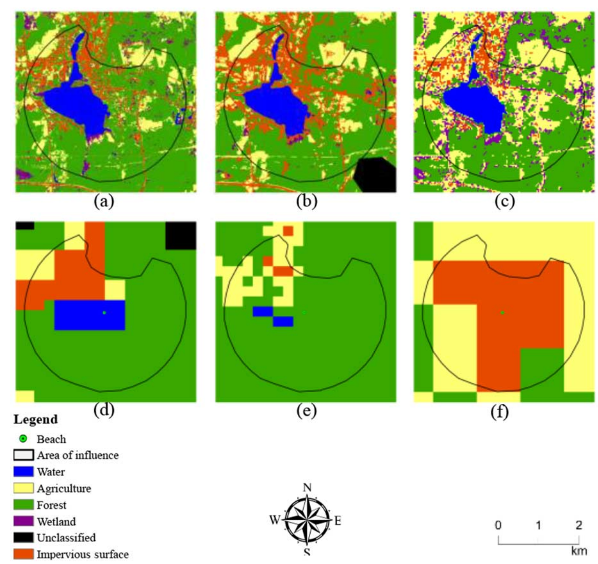

Fig. 5. Detection of environmental determinants in the area of influence of beaches according to the sensors. (a) Classified image of WorldView-2 (1.84 m). (b) Classified image of SPOT-5/HRG (10 m). (c) Classified image of Landsat-5/TM (30 m). (d) Classified image of Envisat/MERIS (300 m). (e) Classified image of Terra/MODIS MOD09GA (500 m). (f) Classified image of NOAA/AVHRR (1100 m).

B. Detection of Environmental Determinants in the Area of Influence

Classification accuracy statistics alone are not enough to evaluate the sensors' classification performance in the context of monitoring environmental determinants in the beaches' areas of influence. A good estimation of the surface occupied by the environmental determinants in the area of influence of the beaches is an essential criterion for the use of EO systems for monitoring the risk of microbial contamination. Fig. 5 compares the classification results for the six (6) EO systems. Comparing the areas of environmental determinants provided by the reference sensors and the evaluated sensors showed that the medium and low spatial resolution sensors strongly overestimate or underestimate the surfaces occupied by certain environmental determinants in the area of influence. For example, differences in area of over 400% are observed with

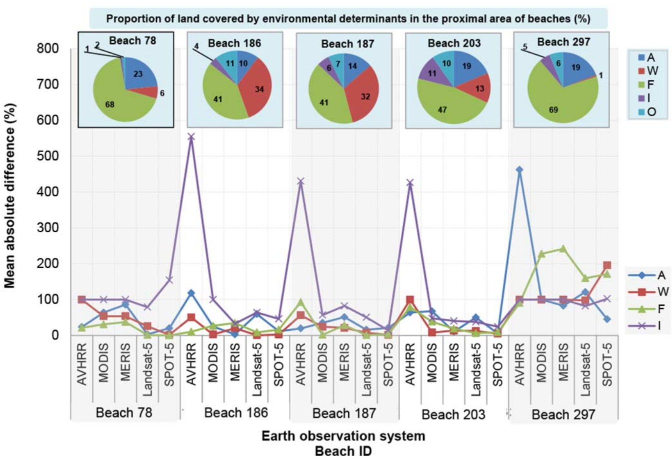

Fig. 6. Mean absolute difference between the proportion of surface occupied by environmental determinants estimated with the evaluated sensors and those which have been estimated with reference sensors in the area of influence of beaches. A, agricultural land; F, forest; I, impervious surface; W, water; and L, wetland.

the estimation of impervious surfaces using NOAA/AVHRR (Fig. 6). Since a good estimate of the area occupied by environmental determinants in the proximal zone of the beaches is an essential criterion for the use of EO systems in the monitoring of these determinants, these data types are therefore not suitable for the estimation of environmental determinants of recreational water bodies. Surface areas estimated using SPOT-5 and Landsat-5 images produce the greatest similarity with reference data, with correlation coefficients, respectively, ranging between 0.88 and 1.00, and between 0.57 and 0.98 according to environmental determinants (Table V). A high concordance was reported by Taylor *et al.* [63] between very high spatial resolution classified image (Quickbird) and high spatial resolution classified images (Landsat-5 and SPOT-5). Andréfouët *et al.* [65] also showed that high spatial resolution sensors (Landsat-7 and SPOT-5) allow a better estimation of the areas occupied by landscape parameters, whereas low spatial resolution sensors (SeaWiFS, 1 km) are not suitable to characterize these areas when they are under 70 km^2. This was the case of most of wetlands in our study area. In addition, the areas of influence of beaches are much lower than 70 km^2 ($\leq 4\ \mathrm{km}^2$). There were not enough areas of influence related to Radarsat-2 and SPOT-5/Radarsat-2 multisensor image to be able to evaluate the estimation of the surface occupied by the environmental determinants in the area of influence and their correlation with reference data. The statistical relationship between fecal contamination and environmental determinants was also not performed for these types of image.

C. Statistical Relationship Between Fecal Contamination and Environmental Determinants

Following logistic regression analyses, we identified two land uses associated with a greater risk of having a higher level of fecal coliforms: one from farming activities and another from urban activities. These activities are known to affect surface water quality [16] and extensive discussion on these findings can be found in Turgeon *et al.* [17]. Percentage of agricultural lands in the area of influence (%AL) and percentage of impervious surfaces (%IS) in the area of influence were the two variables found statistically significant in logistic regression models, but not in all models. Table VI shows those variables for models associated with each sensor, the corresponding odds ratios, and the area under the ROC curve. Among evaluated EO systems, Landsat-5 performed best in terms of statistical models linking the level of fecal contamination of beaches to environmental determinants, with areas under the ROC curve of 0.76 and 0.78 and odds ratios statistically significant for both %AL and %IS. If the area under the ROC curve is large, we can conclude that the model performs well in terms of its capacity to predict the right beach category.

TABLE V
CORRELATION BETWEEN THE ENVIRONMENTAL DETERMINANTS ESTIMATED WITH THE EVALUATED SENSORS AND THOSE WHICH HAVE BEEN ESTIMATED WITH REFERENCE SENSORS IN THE AREA OF INFLUENCE OF BEACHES

EOS	Correlation coefficient			
	A	F	I	L
SPOT-5	0.98	0.95	1.00	0.95
Landsat-5	0.98	0.95	0.98	0.79
MODIS	0.90	0.76	0.58	ND
MERIS	0.74	0.83	0.86	ND
AVHRR	0.81	0.67	0.79	ND

EOS, earth observation system; A, agricultural land; F, forest; I, impervious surface; L, wetland; ND, not determined.

TABLE VI
GOODNESS-OF-FIT OF THE STATISTICAL MODELS ESTABLISHING THE RELATIONSHIPS BETWEEN ENVIRONMENTAL DETERMINANTS AND LEVELS OF FECAL CONTAMINATION

EOS (year)	NoB	Va	OR	AURC
SPOT-5 (2010)	19	%AL	3.4 (0.3;40.6)	0.64
		%IS	1.9 (0.2;15.7)	
SPOT-5 (2011)	22	%AL	1.1 (0.1;8.8)	0.71
		%IS	8.4 (0.8;136.3)	
Landsat-5 (2010)	78	%AL	4.9 (1.2;21.1)	0.78
		%IS	4.9 (1.2;21.1)	
Landsat-5 (2011)	71	%AL	6.3 (1.7;22.6)	0.76
		%IS	3.1 (0.9;10.7)	
MODIS (2011)	78	%AL	6.6 (2.0;21.8)	0.76
		%IS	3.4 (1.1;10.8)	
MERIS (2011)	67	%AL	2.6 (0.7;10.4)	0.73
		%IS	5.7 (1.6;20.6)	
AVHRR (2011)	69	%AL	6.3 (2.1;18.9)	0.70

EOS, earth observation system; NoB, number of beaches; Va, variables; OR, odds ratios; AURC, area under the ROC curve; %AL, percentage of agricultural lands in the area of influence; %IS, percentage of impervious surfaces in the area of influence.

D. Evaluation of EO Systems

Table VII shows the score assigned to the EO systems according to each evaluation criterion. As mentioned above, all the sensors provide a good classification accuracy of environmental determinants. The use of new indices to enhance the separability of thematic classes has greatly contributed to this performance. Only high spatial resolution systems like Landsat-5 and SPOT-5 provide a good detection of environmental determinants in the area of influence of the beaches. This

TABLE VII
COMPARISON OF EARTH OBSERVATION SYSTEMS ACCORDING TO EVALUATION CRITERIA

EOS	Score of evaluation criteria (1–5)								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
S5	3	5	5	5	1	2	2	2	3
L5	5	5	5	5	5	3	1	3	4
MODIS	3	4	1	2	5	5	3	5	5
MERIS	3	4	2	3	5	5	2	4	4
AVHRR	1	4	1	2	5	5	5	4	4
R2	N/A	4	N/A	N/A	5	1	5	1	1

Low score 1 2 3 4 5 High score

EOS, earth observation system; S5, SPOT-5; L5, landsat-5; R2, radarsat-2; C1, performance in statistical models; C2, accuracy of the images classification; C3, detection of environmental determinants in the area of influence; C4, correlation with very high spatial resolution sensors; C5, cost of the images; C6, imaging swath; C7, revisit interval; C8, hours of work; C9, expertise and material required to process the images; N/A, not evaluated.

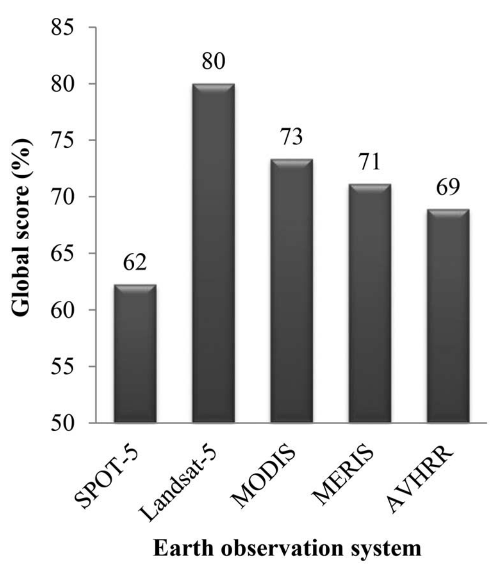

Fig. 7. Global score of the performance of Earth observation systems to estimate environmental determinants in the area of influence of beaches.

criterion is very important for beach monitoring programs that intend to integrate environmental determinants derived from EO. Criteria C5 to C9 (Table VII) have a very practical implication for the use of EO images in these monitoring programs. MODIS images best meet these criteria. However, this sensor does not allow proper detection of environmental determinants in the area of influence of the beaches, and it performs less well in the statistical models. The Landsat-5 system is one that performs best in the statistical models. It provides the best cost benefit among high spatial resolution sensors (Table VII). This higher cost-benefit was also reported by Taylor *et al.* [63]. However, like other high spatial resolution sensors, it requires more time of work given the number of images to be processed to cover the study area. Considering the cost of the images and the number of images required to cover the study area, very few beaches have been studied with SPOT-5 images. This could reduce the performance of the sensor in the statistical models. Only a few criteria were evaluated for Radarsat-2 because of the low number of lakes covered by the image used.

Following the comparison of EO systems, Landsat-5 offers the best compromise to estimate environmental determinants in the context of monitoring the risk of microbial contamination of recreational waters (Fig. 7).

IV. CONCLUSION AND PERSPECTIVES

Our study shows that EO images can be used to assess and monitor environmental determinants that can be associated with a greater risk of fecal contamination of recreational waters. The evaluation of various EO systems showed that Landsat-5/TM images present several advantages compared to other sensors, with the highest accuracy in estimating environmental determinants, the best statistical performance, and the best accessibility (data are free, unlike SPOT-5/HRG images). The data from this sensor, and probably those of its successor Landsat-8/OLI, lend themselves better to monitoring surface conditions and assessing the risk of microbial contamination of recreational waters. However, there are limitations to the use of optical images, the most significant in our study being cloud cover. It routinely reduces the availability of data and the estimation accuracy of environmental determinants. The classification SPOT-5/Radarsat-2 multisensor image allowed us to take advantage of the increased discrimination capabilities offered by panchromatic, multispectral, and radar images. This enabled a better estimation of environmental determinants with a better spatial resolution. However, the implementation of this classification approach required a major effort of spatial integration of optical and radar images. The use of multitemporal imagery, radar technology, multisensor approaches, and the advent of EO satellite constellations like the next Canadian RADARSAT Constellation Mission (RCM) could reduce the limitations of optical images, and make the use of EO an essential approach in the assessment and monitoring of public health risks related to the environment. Further analysis is currently underway, which integrates these data with optical imaging in a multitemporal framework. This study served as a springboard to a greater EO initiative on the microbial hazards associated with recreational waters. Research projects from this initiative helped to develop intersectoral and interdisciplinary frameworks for sustainable actions necessary in the prevention and control of infectious diseases related to the environment. This enhanced interdisciplinary capacity called "Health Remote sensing" is perhaps the most important and lasting benefit of this CSA-GRIP investment.

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