A Review on Extraction of Lakes from Remotely Sensed Optical Satellite Data with a Special Focus on Cryospheric Lakes

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Abstract

Water on the Earth's surface is an essential part of the hydrological cycle. Water resources include surface waters, groundwater, lakes, inland waters, rivers, coastal waters, and aquifers. Monitoring lake dynamics is critical to favor sustainable management of water resources on Earth. In cryosphere, lake ice cover is a robust indicator of local climate variability and change. Therefore, it is necessary to review recent methods, technologies, and satellite sensors employed for the extraction of lakes from satellite imagery. The present review focuses on the comprehensive evaluation of existing methods for extraction of lake or water body features from remotely sensed optical data. We summarize pixel-based, object-based, hybrid, spectral index based, target and spectral matching methods employed in extracting lake features in urban and cryospheric environments. To our knowledge, almost all of the published research studies on the extraction of surface lakes in cryospheric environments have essentially used satellite remote sensing data and geospatial methods. Satellite sensors of varying spatial, temporal and spectral resolutions have been used to extract and analyze the information regarding surface water. Multispectral remote sensing has been widely utilized in cryospheric studies and has employed a variety of electro-optical satellite sensor systems for characterization and extraction of various cryospheric features, such as glaciers, sea ice, lakes and rivers, the extent of snow and ice, and icebergs. It is apparent that the most common methods for extracting water bodies use single band-based threshold methods, spectral index ratio (SIR)-based multiband methods, image segmentation methods, spectral-matching methods, and target detection methods (unsupervised, supervised and hybrid). A Synergetic fusion of various remote sensing methods is also proposed to improve water information extraction accuracies. The methods developed so far are not generic rather they are specific to either the location or satellite imagery or to the type of the feature to be extracted. Lots of factors are responsible for leading to inaccurate results of lake-feature extraction in cryospheric regions, e.g. the mountain

shadow which also appears as a dark pixel is often misclassified as an open lake. The methods which are working well in the cryospheric environment for feature extraction or landcover classification does not really guarantee that they will be working in the same manner for the urban environment. Thus, in coming years, it is expected that much of the work will be done on object-based approach or hybrid approach involving both pixel as well as object-based technology. A more accurate, versatile and robust method is necessary to be developed that would work independent of geographical location (for both urban and cryosphere) and type of optical sensor.

Keywords

Cryospehere, Remote Sensing, Semi-Automatic Extraction, Lakes, Spectral Index Ratio

1. Introduction

Water on the Earth's surface is an essential part of the hydrological cycle. Water resources include surface water, groundwater, inland water, rivers, lakes, transitional waters, coastal waters and aquifers [1]. In this study, we are essentially looking at the extraction of information on lakes because water resources have been degraded and exhausted in last few years. It is necessary to understand the changes in spatial extents of water resources. Lakes are inland bodies of standing water. Lakes are an essential component of the hydrological cycle and hence key tools for the management of water resources [2]-[4]. Although millions of lakes are scattered over the earth's surface, most are located at higher latitudes and mountainous areas. Lakes may be classified according to their manner of formation or characteristics (**Table 1**). Lakes can be formed by glaciers, tectonic plate movements, river and wind currents, and volcanic or meteorite activity. Some lakes are only seasonal, drying up during parts of the year. All lakes are either open or closed. If water leaves a lake by a river or other outlet, it is said to be open. If water leaves a lake only by evaporation, the lake is closed. Closed lakes usually become saline. Lakes usually show circular, semi-circular or elongated shape. Understanding and evaluating lake dynamics is necessary to conduct the sustainable management of water resources [5]. In addition, lake surface areas (especially closed lakes) are sensitive to natural changes and thus may serve as significant proxies for variations in regional environmental and fluctuations in global climate [3] [6]. Changes in the areal extent of lake surface water may occur due to various factors, including the progressive unveiling of the lake basin by sediments, climate change, tectonic activity causing uplift or subsidence, and the development of drainage faults [7] [8]. Being able to access the spatial distribution and geographical extent information on lakes in real time has great significance in limnology and for understanding interactions between regional hydrology and climate change [9]. Satellite remote sensing (RS) has advantages because it can track land surface information in real-time macroscopically, multitemporally, multispectrally, dynamically, and repetitively; hence, it is appropriate for surveying and mapping surface water bodies [10]. The present review especially focuses on the broader category of cryo- spheric lakes and their extraction using optical RS methods. The cryosphere refers to those parts of the Earth containing water in its frozen state: snow, glaciers, permafrost, seasonally frozen ground, lake and river ice, sea ice, ice sheets, and shelves. The cryosphere holds a significant amount of the Earth's total supply of freshwater. About 77% of Earth's freshwater is frozen, 91% of which is contained in the Antarctic ice sheet, 8% in the Greenland ice sheet, and the remaining 1% is contained in glaciers [11]. Many studies and research works have been carried out on cryospheric lakes in order to track environmental changes and behavior. Cryospheric lakes are classified into 5 types as depicted on **Table 2**. Inclement weather in the polar regions (Arctic and Antarctic), few numbers of fine-weather days in summer, and high logistic cost restricts research trips to polar Regions. Therefore, satellite RS data and aerial photography are important sources of information for monitoring the short-term and long-term changes that occur at a specific location in cryospheric regions over time. Although RS data can never replace aerial photographs, which provide images at a resolution as high as 0.2 - 0.3 m, it is suitable for lake-feature extraction in the cryospheric regions, where frequent aerial photography is difficult because of the extremely harsh environment and the high logistical costs. Hence, development of automated or semi-automated feature extraction methods using RS data is much needed for continuous monitoring of the geographical features in a cryospheric environment.

Table 1. Types of lakes (Source: [12]).

Type of lake	Description	Examples
Artificial lake	They may be constructed for various purposes, such as hydroelectric power generation, recreation, industrial use, agricultural use, or domestic water supply.	Lake Mead and Lake Powell, USA
Crater lake	A lake that is formed in a volcanic crater after the volcano has been inactive for some time. Lake water may be fresh or highly acidic and may contain various dissolved minerals.	Mount Aso crater lake, Japan Taal Volcano, Phillippines
Endorheic lake	A lake that has no significant outflow, either through rivers or underground diffusion.	Lake Eyre, central Australia, Aral Sea in central Asia
Fjord lake	A lake in a glacially eroded valley that has been eroded below sea level.	Geirangerfjord, Norway Tracy Arm fjord, Alaska
Former lake	Prehistoric lakes and those that have permanently dried up through evaporation or human intervention.	Owens Lake in California, USA
Underground lake	A lake that is formed beneath the surface of the Earth's crust. Such a lake may be associated with caves, aquifers, or springs.	Reed Flute cave, China Lake Vostok, Antarctica
Seasonal lake	A lake that exists as a body of water during only part of the year.	Badhkal lake and Sambhar lake, Rajasthan, India
Oxbow lake	Characterized by a distinctive curved shape, it is formed when a wide meander from a stream or a river is cut off.	Gambi lake on River Tana, Kenya
Lava lake	This term refers to a pool of molten lava in a volcanic crater or other depression. The term lava lake may also be used after the lava has partly or completely solidified.	Erta Ale, Ethiopia Nyiragongo, Democratic Republic of the Congo

Table 2. Types of cryospheric lakes (Source [13]).

Type of lake	Description	Examples
Supraglacial/Epiglacial lakes (SGLs)/	The lakes formed over the glacial surface due to the processes active on the glacial surface. Shifting, merging, and draining are characteristics of SGLs. SGLs are more dynamic and vary in time and space.	SGL on Milam glacier
Open lake (Landlocked lakes)	A body of water that is surrounded completely by land. A landlocked lake has no water source such as a river. It is fed by water seepage in the ground and water runoff with the surrounding land.	Lake Vanda in Antarctica
Epishelf lake	When ice shelves completely block the mouth of a fjord, an epishelf lake is created. This is caused by melt water that flows into the fjord every summer, but is impounded behind the ice shelf.	The largest epishelf lake, Disraeli Fiord, Arctic Ocean.
Pro-glacial lake	Pro-glacial lakes are ice-contact lakes occurring adjacent to the frontal margin/snout of a glacier. Many such types of lake are ice-core moraine-dammed or ice-dammed and show ephemeral or perpetual nature.	Vasundhara Tal at Raikana glacier, Himalayas
Moraine-dammed lake	A lake formed as a glacier recedes from its terminal moraine, the moraine acting as an unstable dam. Most of these lakes are formed when valley and cirque glaciers retreated from advanced positions achieved during the Little Ice Age.	Laguna Paron, Peru

2. Brief Review on RS Methods Used for Lake Feature Extraction

A brief review of the most commonly used methods employed in mapping of water feature from urban and cryospheric regions is depicted in **Table 3** and **Table 4**. Optical satellite systems have most frequently been applied to lake or water body extraction research. The parts of the electromagnetic (EM) spectrum covered by these sensors include the visible and near-infrared (NIR) ranging from 0.4 to 1.3 μm, the short wave infrared (SWIR) between 1.3 and 3.0 μm, the thermal infrared (TIR) from 3.0 to 15.0 μm and the long wavelength infrared (LWIR) from (7 - 14 μm). The decision tree and programming method are used for extracting water body information from the flood affected region [14]. The semi-automated change detection approach is used for extracting water feature form satellite image [15]. An automatic extraction method is used for extracting water body from IKONOS and other high resolution satellite image [16]. Thresholding and multivariate regression method [17], a conceptual clustering technique and dynamic thresholding [18], an original entropy-based me-

Table 3. Methods used for extraction of urban lakes.

Satellite Used	Study area	Methods	Advantages
Landsat 5 (TM) Landsat 7 (ETM+) Landsat 8 (OLI) Resolution: 30 m [35]	Lake Urmia located in the northwest of Iran	Normalized Difference Water Index (NDWI) and Principal Component Analysis (PCA)	NDWI performed slightly better than the NDWI-PCs. NDWI-PCs have an advantage over the NDWI, that it detects the surface water changes of two and three different times simultaneously by applying a single threshold to the selected PC.
Landsat TM ETM+ Resolution: 30 m [36]	Rift Valley lakes in Kenya	Water Index (WI) using Tasseled Cap Wetness (TCW) index and NDWI	WI detected the shorelines with an accuracy of 98.4%, which was 22.3% higher than the TCW, and 43.2% more accurate than the NDWI.
Landsat 4 - 5 Resolution: 30 m [37]	Huanghe river delta, China	$B2 + B3 > B4 + B5$ $B4 < 60$ $B4 > B5$ and $B5 < B2$	The decision tree algorithm failed to extract small water bodies at scales below the sensor resolution.
Landsat TM and ETM+ Resolution: 30 m [38]	Hebei, Jiangxi, Ningxia, China	A watershed segmentation method is adopted to detect mixed water pixels at the edges of lakes or rivers	Automatic method for extracting rivers and lakes (AMERL) successfully extracted most of the narrow rivers and lakes.
SPOT 4 Resolution: 10 m [39]	Jiangning county of Jiangsu, China	Decision Tree (DT) model based on both spectral and auxiliary information of Digital Elevation Model (DEM) and Slope (DTDS).	It is difficult to extract water bodies effectively by applying a single technique due to effects of shadows. Unsupervised classification yields result with low accuracy.
Landsat 5 TM Resolution: 30 m [40]	Murrumbidgee, Wagga Wagga, Australia	Single band density slicing and Maximum Likelihood (MXL).	MXL proved to be more accurate than density slicing to detect water bodies. Density slicing yielded a less speckled output image as compared to MXL.
Landsat 5 TM Resolution: 30 m [41]	Denmark, Switzerland, Ethiopia, South Africa, New Zealand.	$AWEI_{Sh} = Blue + 0.25*Green - 1.5 * (NIR + SWIR1) - 0.25 * SWIR2$ $AWEIN_{Sh} = 4 * (Green - SWIR1) - (0.25 * NIR + 2.75 * SWIR2)$	Automatic Water Extraction Index (AWEI) successfully extracted surface water with high accuracy, particularly in mountainous regions where hills cast shadows on background surfaces and in urban areas with complex land cover. It is a simple technique to extract water in different environmental conditions.
MODIS (250 - 500 m) and ASTER (15 - 90 m) [42]	Bihor, Romania	Threshold method and supervised classification	This approach is useful in providing information about water classification from different resolution data.
ASTER (15 m) and MODIS [43]	Koros basin, Roma-nian-Humgarian border	$NDVI = \dfrac{R0.87 - R0.66}{R0.87 + R0.66}$ Band 1 (0.66 μm) - 250 m Band 2 (0.87 μm) - 250 m	Cloud shadow and water pixels are not completely separated out.
ASTER Resolution: 15 m [44]	Beijing, China	4 segmentation levels were created for differentiation between water, vegetation and non-vegetation	Accuracy of object-oriented classification is higher than the accuracy of MXL classification.

Table 4. Methods used for extraction of cryospheric lakes.

Satellite Data	Study area	Specifications	Remarks
Landsat (30 m) and ASTER (15 m) [71]	Gangotri glacier, Himalayas	$NDWI = \dfrac{NIR1 - blue}{NIR1 + blue}$ $ASTER\ ratio = \dfrac{Green}{NIR}$	Results led to the accurate identification of glacial lakes using the NDWI. Lake identification based on ASTER dataset is slightly more accurate than Landsat dataset.
World View 2 (WV2) (2 m) [72]	Greenland Ice Sheet (GrIS)	$NDWI = \dfrac{blue - red}{blue + red}$	The slush elimination process was not accurate, but it can be made accurately by fusing morphological procedures using edge detection with multi-threshold procedures (accuracy = 85.2%).

Continued

WV2 (2 m) [73] [74]	Larsemann Hills, Antarctica	$NDWI1 = \dfrac{Coastal - NIR\,2}{Coastal + NIR\,2}$ $NDWI2 = \dfrac{Coastal - NIR\,1}{Coastal + NIR\,1}$ $NDWI3 = \dfrac{Blue - NIR\,1}{Blue + NIR\,1}$ $NDWI4 = \dfrac{Blue - NIR\,2}{Blue + NIR\,2}$	NDWI-based indices approach offers several advantages as it is consistent in extracting water bodies against noise, flexible as the threshold values can be adjusted to remove background noise by not affecting the target extraction, time efficient in processing and producing the output and comparatively easier to implement.
Landsat ETM+ (15 m and 30 m) [75]	Lake Merzbacher, border of China	$NDWI = \dfrac{NIR - Blue}{NIR + Blue}$ Threshold 0.35 to 0.55 To accurately extract area of floating ice, ratio is used: $\dfrac{NIR}{Red}$	Results show that the index can predict the outburst process of the lake and determine the outburst period of the lake after its drainage had occurred. The automatic program is not so perfect due to the Interferential factors such as snow or spissatus in images (accuracy= 92.0%).
Landsat TM and SPOT (Fused 10 m) [76]	Swiss Alps	$NDWI = \dfrac{NIR - Blue}{NIR + Blue}$ $NDWI = \dfrac{TM4 - TM1}{TM4 + TM1}$ Simple channel ratio: $\dfrac{TM4}{TM1}$	TM4 and TM1 bands can be replaced by TM5 and TM7, but TM4 and TM1 are capable of discriminating water from snow and ice more accurately. The simple channel ratio works well, but NDWI showed an enhanced contrast between water and surrounding environment.

thod [19], are also used for extraction of water bodies. The water body can be extracted by classification; unsupervised classification [20]; the support vector machine (SVM) with one-against-one (1A1) and one-against-all (1AA) techniques are used for land cover mapping [21]. A supervised classification algorithm [22] of RS satellite image that uses the average fuzzy intra-cluster distance within the Bayesian algorithm [23]; sometimes combinations of supervised and unsupervised classification [24] are used for water information extraction. A new index normalized optical water index (NOWI) was proposed to accurately discriminate between land and water regions in multi-spectral satellite imagery data from DubaiSat-1 [25].

3. Importance of Cryospheric Lakes

Lake ice cover has been established as a robust indicator of local climate variability and fluctuations. Lake ice forms an essential component of the cryosphere, especially at high mountainous latitudes where a large number of lakes exist. Long-term records of lake ice have been significantly used as a proxy indicator of winter climate conditions. Previous studies have identified lake ice as a highly sensitive cryospheric component to climatic conditions [26]. Spatio-temporal changes in lake ice cover have an imperative feedback on energy exchanges between the lake surface and the atmosphere. Persistent warmer air temperatures [27] and raised snowfall had been observed in the Arctic over the last decades [28], and found to be associated with an amplified reduction of sea-ice concentrations, thickness and extent [29], which had been accelerated during recent years [30]. These spatio-temporal changes in the Arctic climate system have likely had an impact on ice phenology of lakes in coastal regions adjoining to the Arctic Ocean. SGLs play an important role in establishing hydrological connections that allow lubricating seasonal meltwater to reach the base of the ice sheet [33] [34].

Among all components of glacier system, SGLs are the most straightforward to be recognized. SGLs have already been researched on the Greenland ice sheet, Svalbard, and Himalaya. SGLs on Greenland characteristically form as a response to summer melting. SGLs typically form below 1500 m altitude, in topographic low regimes in the ablation zone and can expand to numerous kilometers in size on the surface of the Greenland ice sheet. SGLs can also form in the lower ablation area of debris-covered valley glaciers. The life span of SGLs is unpredictable and *in situ* monitoring is less practical. Hence, RS can be effectively used for studying SGLs and their seasonal variations to address the status of glacier or ice sheet. SGLs and firn aquifers store a substantial amount of meltwater, providing a buffer between melting and mass loss to the ocean [31] [32].

4. RS for Extracting Cryospheric Lake Features

To our knowledge, almost all of the published works on an extraction of surface lakes in cryospheric environments have used the satellite RS data. Multispectral RS has been widely utilized in cryospheric studies and have employed a variety of electro-optical satellite sensor systems for characterization and extraction of various cryospheric features, such as glaciers, sea ice, lakes and rivers, the extent of snow and ice, and icebergs. Aerial photography of ice-covered terrain began during the early 20th century by expeditions to the high altitudes and was used primarily to document the progress of the expedition. Wilkins documented ice cover in the Antarctic Peninsula during the first successful flight in Antarctica by using a handheld, folding Kodak 3A camera [45] [46]. The quality of the photographs is often exceptional, but the reason behind opting for satellite RS instead of aerial photography is the harsh environment of cryosphere where frequent monitoring is difficult by the use of aerial photography which adds up to high logistics costs. Cryospheric RS applications initiated as early as 1962 with the launch of the Argon satellite. Thereafter, in the 1970s Landsat 1, 2, and 3 Multi-Spectral Scanner (MSS) images constituted an important glaciological resource [47]. Initial successes in large-scale mapping were achieved through the use of the moderate spatial resolution (1 - 2.5 km) and wide swath (2400 km) advanced very high resolution radiometer (AVHRR) images, [48] which helped reveal details about ice stream flow in West Antarctica [49]. After the original AVHRR mosaic of Antarctica, the United State Geological Survey (USGS) made subsequent improvements to the mosaic by eliminating more clouds, separating the thermal band information to illustrate surface features more clearly, and correcting the coastline of the mosaic to include the grounded ice while excluding thin, floating fast ice [50]. Another large-scale mapping has been completed with MODIS for both the Arctic and the Antarctic [51]. Most recently, Landsat imagery of Antarctica has been compiled into a single, easily accessible map-quality data set [52] and SPOT stereo imagery have been used to derive DEM of ice sheets, ice caps, and glaciers [53]. In the snow and glaciated terrain of the Himalayas, satellite RS was established as the best tool because many of the glacial lakes are located at very high altitude, cold weather, and rugged terrain conditions, making it a tedious, hazardous and time-consuming task to monitor by conventional field methods. Satellite RS technology facilitates the study of initial and qualitative hazard assessment of glacial lakes of the Himalayas systematically with a cost-to-time benefit ratio [13].

   Cryospheric lake features have been researched primarily by means of multispectral satellite images from the ASTER [54] [55], Landsat-7 [56], and MODIS imagery [57] instead of aerial photography despite its very high spatial resolution. The relatively high spectral reflectance response from a water body feature in the ASTER, MODIS, and Landsat multispectral bands is the foundation for employing these sensors in water body mapping and surveying applications. An accurate manual delineation of lake extent is used [55] [58] [59] when lakes are easily identifiable on images. Applications of methods that discriminate water from surrounding ice and snow are possible on optical images using semi-automatic methods that employ different spectral bands of the satellite sensors [60]-[62]. Many research studies have surveyed methods for semi-automatic or automatic lake feature extraction using medium and coarse resolution satellite RS data (e.g., [57] [63] [64]). Automated or semi-automated methods have the advantage of rapid extraction of lakes from multi-temporal images with large areal coverage [57] [62]. Although manual delineation is highly accurate [65], it is time-consuming and thus unsuitable for wide geographical areas. Therefore, accurate manual delineation is preferable for studies over smaller areas, but studies that encompass larger areas would benefit from automatic or semi-automatic methods [63]. The most common method for deriving surface water bodies from satellite images is the density slice method, which uses single or multiple spectral bands, and multi-spectral classification [66] [67]. Frazier and Page reviewed numerous methods employed by various authors to extract water bodies from Landsat TM and MSS image classifications [40]. Yu *et al.* [68] investigated and discussed a few methods for deriving water information using SPOT-4 images. The thresholding and multivariate regression method, a conceptual clustering technique, the dynamic thresholding method, and entropy-based method, have been successfully implemented in surface water extraction studies [17] [18]. The water body features can be extracted by unsupervised classification [20], supervised classification (e.g., a Bayesian algorithm) [23], and a combination of both supervised and unsupervised classification [24]. Waldemark *et al.* [69] proposed a neural network (NN) approach for extracting water bodies from satellite images. In addition to the aforementioned water classification methods, there are several other original methods, such as the Decision Tree (DT) method and the step iterative method [39] [70]. It is evident that the most common methods for extracting lakes are, single band–based threshold methods, spectral index ratio (SIR)-based multiband methods, image segmentation methods, spectral-matching methods, and supervised target detection methods.

SIRs are utilized to extract a specific target or feature, and they are computed from the difference in reflectance values of the bands used to formulate the ratio [77]. Conventionally, water and vegetation have been the primary focus of normalized difference SIRs because they are simple to classify based on the difference in reflectance values, ranging from 450 nm to 750 nm. Presently, the methods for extracting lakes are based on a spectral index or multiband techniques, which are spectrum property–based methods [78], such as the NDVI [79] and NDWI [80]-[83]. Since a single spectral index could not demarcate lakes effectively in different environments, many improved indices have been proposed to yield better results in specific environments [84]. Ouma and Tateishi [36] proposed a novel water extraction index for shoreline delineation by combining the TCW index (TCWI) and the NDWI.

A comprehensive water body information extraction technique was proposed by Wu *et al.* [85] through the fusion of the spectral relationships between various bands with supervised classification methods. Rogers and Kearney [86] proposed the NDWI for medium spatial resolution and high temporal resolution with MODIS multispectral satellite images (MSI). Furthermore, Xiao *et al.* [87] proposed a land surface water index (LSWI), while Mo *et al.* [88] proposed a mixed water index (MWI) by combining the NDVI and NIR data to identify water bodies in MODIS images. Lu *et al.* [89] recommended an integrated water body extraction technique with HJ-1A/B satellite imagery by utilizing differences between NDVI and NDWI. These modified indices have been commonly used to map surface water bodies using Landsat and MODIS images [90]-[97]. These indices are normalized, ranging from −1 to 1, in which zero acts as a threshold to discriminate water from vegetation and land surface. However, because of the complexity of cryospheric environments, various ground targets may have the same spectrum characteristics. Therefore, only one type of spectral index method cannot extract water bodies under all environmental conditions [98].

5. RS Methodologies for Extracting Lake Features

Methodologies of a lake or water body extraction can be summarized into three groups: feature extraction using pixel-based and object-based classification, and SIRs. Nath and Deb [66] provided a comprehensive overview of methods for water extraction from high resolution satellite images. June *et al.* [37] developed an automatic extraction of water bodies from a Landsat TM image using DT algorithm. The proposed algorithm was based on spectral characteristics of the water body in TM images. Wang *et al.* [99] developed water extraction method based on texture analysis. Luo *et al.* [100] developed an algorithm for water extraction using Landsat TM which combines water index computation, whole-scale segmentation, whole-scale classification and local scale segmentation and classification to achieve highly-precise water extraction result [101]. The traditional pixel based digital image classification has been and is still being used for characterization and mapping the spatial extent of forests, urban, water bodies, coastal, and wetland areas [102]. In principle, three types of classification methods exist, namely unsupervised, supervised and hybrid [103]. Unsupervised classification clusters pixels in a dataset based on statistics only, without any user-defined training classes. The most commonly used unsupervised land cover/land use (LC/LU) classifier is the Iterative Self-Organizing Data Analysis (ISODATA) classification algorithm. On the other hand, several types of statistics-based supervised classification algorithms have been developed. Examples of the more popular classifiers (in increasing complexity) are parallelepiped, minimum distance, MXL, and Mahalanobis distance [104]. Hybrid methods can combine the advantages of manual, parametric and non-parametric methods in various combinations to optimize the classification process [105]. Object-based Image Analysis (OBIA), a recent image analysis approach appears to be more popularly used for the classification of LC/LU of urban areas [106]. Object-based method considers image classification based on objects such as topologic (neighborhood, context) and geometric (form, size) information [107]. The object-oriented approach analyzes objects within images as a processing unit instead of using pixels. Geographic object-based image analysis (GEOBIA), as opposed to pixel-based image processing, is also emerging as a popular classification method [108]. Studies that monitored extreme cold areas using new satellite sensors were initiated by using medium and low spatial resolution images [109]. Sundal *et al.* [62] proposed an automatic method based on a set of fuzzy logic membership functions to identify and map lakes. The method used a single threshold developed by Box and Ski [60] to differentiate between meltwater and ice, exploiting the different sensitivity to water of MODIS bands 1 and 3. Certain types of lakes, such as deep lakes, were particularly hard to identify. A semi-automatic method to track lakes was developed by Selmes *et al.* [57]. Liang *et al.* [64] developed an automatic method for lake identification, mapping, and tracking. Exploiting the characteristics of the changing nature of

the lakes and their surroundings, Johannson and Brown [63] developed a method known as Adaptive Lake Classification (ALC); ALC, specifically targeting the identified problem lakes [110]. Methods used for water feature extraction in an urban environment and cryospheric environment are summarized in **Table 5** and **Table 6**.

6. Discussion

We have reviewed various methods utilized for extraction of a lake or water body features in urban and cryospheric environments. In this section, we summarize and discuss the generalized trend in methods, satellite datasets and achieved accuracies for lake feature extraction. **Table 7** depicts different water feature extraction methods and accuracies expressed in kappa value. For extracting urban lakes (or other urban features), per-pixel based approaches were always the primary tool because of their low cost and easy implementation. Per-pixel based classification approach was considered to be the favorite choice of most of the researchers to extract lakes.

Unfortunately, this procedure always resulted in mixed pixel's problem. Pixel based classification approaches on high spatial resolution satellite images (e.g. SPOT, Landsat), often results in "salt and pepper" representation, which is even increasing when considering the new generation of very high spatial resolution data (e.g. IKONOS, QuickBird, GeoEye, WV2 etc.). This problem has led many researchers to incorporate segmentation, texture, context, color, and many other parameters to glide the mixed or wrongly classified pixels into their proper classes [118]. So, to overcome the limitations of pixel-based approach, a new approach was developed known as an object-oriented approach which has gained more and more interest, especially when dealing with very high spatial resolution satellite images to capture the finer details of the urban area. In almost all the case studies, object-based classification approach resulted in improved accuracy ranging from 84% to 89% (approximately). Object-based classification can, not only use spectral information of land types, but also use images' spatial position, shape characteristic, texture parameter and the relationship between contexts, which effectively

Table 5. Technologies used for water body extraction in cryospheric environment.

Satellite data	Method name	Remarks
WV2 (0.5 m) [72]	Automated Spectral-Shape Procedure	Average positional offset between delineated and manually digitized streams is about 1 pixel. $NDWI_{ice}$ was discovered in order to increase the contrast between ice and water. (accuracy = 92.1%).
MODIS (250 m) [63]	ALC approach based on object-oriented classification.	ALC mainly focuses on the changing nature of lakes. Difficulty in detecting small lakes (<0.1 km^2) cannot be resolved. Lakes with partial or total ice cover posed a challenge for ALC as both lake ice and glacier ice have similar reflectance.
ASTER (15 m) [111]	Non-parametric classification, Spectral indices NDWI using green and NIR band, and square pixel metric (SqP) method	99% accuracy attained by applying NDWI, elevation and NIR/Red band ratio to separate water features from ice debris
Landsat (30 m) RADARSAT (7 m) [112]	Supervised MXL Classification	Difficulty in mapping small ponds which can be overcome by using high resolution imagery or a high resolution aerial photograph. User's accuracy for water class = 95%.
MODIS (250 m) ASTER (10 m) Landsat ETM+ (10 m) [113]	Lakes were delineated automatically using object oriented segmentation and classification methods [57] [62] [63] [110].	Sundal [110] had difficulty in resolving ice-covered lakes. Johannson and Brown [63] reported that as many as 18% of reported SGLs are likely to be false positive. In Selmes *et al.* [57] any lake <0.125 km^2 does not feature in the dataset. It is found to report lake area most accurately.
WV2 (0.5 m) [77]	Spectral indices using customized NDWIs having Coastal and Blue band against NIR1 and NIR2	The coastal band produced less false positive results in comparison to the blue band during the detection of lakes. The PAN-sharpening process does affect the accuracy of feature classification.
WV2 (0.5 m) [98]	Support vector machine (SVM), Spectral angle mapper (SAM), MXL, NN classifier, Winner takes all (WTA)	The study concluded that WTA (accuracy = 97.23%) was better for mapping water and land and SVM and NN classifier for mapping snow/ice.
IKONOS (4 m) Hyperion [109]	For improving the accuracy of water classification, IKONOS tasseled cap transformation is applied to wetness	Small lakes were detected due to the high spatial resolution of IKONOS image. The water class was defined by an IKONOS NDVI of greater than −0.1 (accuracy = 86.70%).

Table 6. Technologies used for water body extraction in an urban environment.

Satellite data	Method name	Remarks
Landsat TM (30 m) [114]	Object-oriented classification, Pixel-based supervised MXL.	MXL classification produced salt and pepper image, whereas the classified image derived from polygon-based classification is closer to human visual interpretation.
Landsat TM (30 m) [115]	Supervised MXL classification, Unsupervised ISODATA classification.	Accuracy assessment showed that the ISODATA could multispectrally classify the urban water successfully. Even smaller ponds or rivers (<30 m) can be extracted if the high resolution imagery is used.
Quickbird (0.61 m) [116]	Statistical Regional Merging (SRM) for image segmentation, NDWI and Normalized Saturation-value Difference Index (NSVDI) for water extraction.	The results prove that the accuracy of the extracted water features can be significantly improved and shadows can be effectively eliminated.
Zi-Yuan 3 (ZY-3) (2.1 m sharpened) [117]	Object oriented multi-resolution segmentation, Edge detection using Canny-edge detector.	The extraction results on the high resolution remotely sensed image are significant by taking into account the spectrum geometry and texture information of images. (Accuracy = 94.6%).
Landsat ETM+ (15 m), ERS SAR (26 m), SPOT (10 m sharpened) [19]	Knowledge-based DT method including spatial features as size, shape, position and multi-spectral characteristics.	The proposed algorithm is differentiated from other existing algorithms as it is independent of the image sensor. It can be applied on either PAN images or any spectral band of optical images. The proposed algorithm failed to extract small water areas.
WV2 (2 m) Rapid Eye (2 m) Pleiades (5 m) [103]	Hierarchical land-use classification, ISODATA unsupervised classification to extract additional subclasses.	RapidEye showed a higher overall accuracy of 78%, surpassing the result of Pleiades (74%). Pleiades showed the best classification accuracy compared to RapidEye and WV2. WV2 proves to be more versatile to extract various sub-classes.
WV2 (0.5 m sharpened) [102]	Object-based image classification utilizing Nearest Neighbor decision rules.	The analysis found that object-based classification using scale parameter of 60 produced the best result of wetland delineation compared to scale 30 and 300.

Table 7. Water feature extraction methods with kappa statistics values.

Satellite data	Study area	Method	Kappa value
Landsat TM [37]	Huanghe river delta, China	DT algorithm: TM2 + TM3 > TM4 + TM5 was used to extract reservoirs, ponds and broad rivers	0.92
Landsat 5 TM [41]	Test site 1: Denmark, Test site 2: Switzerland, Test site 3: Ethiopia, Test site 4: South Africa, Test site 5: New Zealand.	AWEI	Test site 1: 0.93 Test site 2: 0.95 Test site 3: 0.97 Test site 4: 0.98 Test site 5: 0.98
Landsat TM and ETM+ [84]	Bayi lake, Fuzhou City, China	Modified NDWI	0.99
ASTER [44]	Beijing, China	An object-oriented approach using Hierarchical classification and DT classification	0.81
Landsat 5-TM Landsat 7-ETM+ Landsat 8-OLI [35]	Lake Urmia, Iran	NDWI-PC	0.73
Quickbird [130]	Phoenix and Scottsdale, Arizona	Object-based approach using multi-resolution segmentation algorithm, Minimum distance supervised classification	Scottsdale: 0.81 Phoenix: 0.82
IRS LISS III and LISS IV [131]	Bhopal, India	NN supervised classification approach	LISS III: 0.98 LISS IV: 0.96
WV2 and Airborne Imaging Spectroradiometer Analysis (AISA) [132]	Study area 1: Turtle Creek Corridor, Dallas, Texas Study area 2: National Mall Area, Washington, DC	Fuzzy Kolmogorov-Smirnov (FKS)	AISA: 0.79 WV2: 0.99

avoid the "salt and pepper phenomenon" and greatly improve the accuracy of classification [119]. After reviewing numerous methods for water feature extraction in the general environment, it is apparent that common water classification methods for optical imagery could be categorized into four basic types [120]: a) thematic classification [121], b) linear un-mixing [122], c) single-band thresholding [123] and d) two-band spectral WI [80] [84] [86]. A Synergetic fusion of various automatic and semi-automatic methods are also proposed to improve water information extraction accuracies. The spectral band method is easy to implement, but frequently misclassify mountain shadows, urban areas or other background noise as lakes [124]. The most notable supervised classification methods used for lake extraction are MXL, DT, artificial NN and SVM [125], while the most common unsupervised classification methods include the K-means and ISODATA [126] [127]. These methods may achieve superior accuracy than spectral band methods under some environmental conditions; however, existing ground reference datasets are required, which restrict these methods from being applied over large study regions [40]. The WIs have been extensively used because of their comparatively high accuracy in lake detection and low-cost implementation [128]. In many WIs, the lack of stability of the threshold is still a problem [120], making it difficult to use uniformly. The lack of a reasonably stable threshold may make the classification more time-consuming and lead to a subjective choice of threshold which may also affect accuracy [41]. The design and implementation of WIs have been persistently improving [38]. Despite the fact that a number of lake extraction methods are published in the literature, the choice of method for a specific application is constrained by accuracy issues. Water classification accuracy problems are especially pronounced in areas where the background land cover includes low albedo surfaces such as shadows from mountains, buildings, and clouds. The occurrence of shadows may cause misclassification because of the resemblance in reflectance patterns, which may hamper the accuracy of the surface water mapping and change analysis [41] [129].

Even if the object-oriented based approach is most widely researched topic in urban applications yet it is not really popular with cryospheric regions [74]. Still cryospheric applications such as feature extraction from cryospheric regions, detailed land-cover classification of cryosphere employ pixel-based approach. These days, for obtaining detailed land-cover classification or for accurate feature extraction from cryospheric region very high resolution optical satellite imagery is being used with the resolution of the order of ~0.5 - 5 m. The popular optical satellites falling in this category are: WV2, SPOT5, IKONOS, GeoEye etc.

Most commonly used methods for lake feature extraction from cryospheric region are:

a) Spectral indices making use of two satellite imagery bands,
b) Supervised classification involving MXL, parallelepiped, NN, SAM and SVM, target, WTA approach
c) Unsupervised classification: involving ISODATA *technique*
d) Target detection methods which include: matched filter (MF), constrained energy minimization (CEM), adaptive coherence estimator (ACE), SAM, orthogonal sub-space projection (OSP) and target-constrained interference-minimized filter (TCIMF)
e) Single band threshold and spectral relation method

Despite so many methods being developed for lake feature extraction, none of them is known to yield highly accurate results in all environments. The methods developed so far are not generic rather they are specific to either the location or the satellite imagery or to the type of the feature to be extracted. Lots of factors are responsible for leading to inaccurate results of lake feature extraction in Cryospheric regions, e.g. the mountain shadow which also appears as a dark pixel, is often misclassified as open lake, which can be corrected using topographical modeling using DEM [133]-[139]. There are various other target features which possess similar spectral characteristics which result in overestimation and thus outputs an inaccurate result. Thus, after knowing the past and present of methods being developed for lake feature extraction, it's felt that there is a strong urge for developing new methods that would yield results with higher accuracy. Also the method should be highly versatile and robust as well as dynamic, so that it can be used for extraction of all types of lakes in all environments under all situations without any change in the design of the method.

7. Summary and Conclusion

Satellite sensors of varying spatial, temporal and spectral resolutions have been used to extract and analyze information regarding surface water. Studies using ASTER and Landsat ETM+ data have focused on smaller regions with a limited number of lakes, mainly using manual delineation of lake extent. For coverage of larger areas MODIS imagery is generally been adopted. ASTER and ETM+ images have a high spatial resolution of

the order of ~10 m, conducive to accurate lake area delineation, MODIS imagery is much coarser i.e. of the order of ~250 m but the temporal resolution of MODIS is higher (at least once a day rather than biweekly). Landsat series of satellites are among the most extensively used multispectral sensors in surface water extraction studies. Medium resolution satellite data (10 - 90 m) are available for cryospheric studies since the early 1970s, with the launch of the new space-borne sensors: Landsat MSS, Landsat TM and ETM+, SPOT, Terra ASTER, IRS, and more recently the Advanced Land Observing Satellite (ALOS) launched in 2006. The other group of optical satellites is high resolution, of the order of a meter and sub-meter: WV2, IKONOS, Quickbird, and Geo Eye-1, are now being brought up in use for the extraction of lakes from the cryospheric environment [140]-[150]. Now a day's much of the work based on cryosphere such as feature extraction and land cover classification employs high resolution imagery because of its high spatial resolution, which enables to achieve finer details of the region, which is otherwise not possible by using medium resolution imagery (e.g. Landsat TM, ETM+, SPOT, ASTER etc.). After reviewing numerous methods available for cryospheric lake feature extraction, we conclude that the most popular and effective method for extracting lake is based upon spectral indices which make use of two optical bands at a time. This method is the most researched and emerging methods because of its high-term advantages which include low implementation cost, simple in understanding, easily modifiable and effective in producing stable output. Despite its potential benefits, it does suffer from few limitations, which include high location or feature dependency which makes it working only for a specific application, high misclassification which usually occurs because of objects possessing similar spectral characteristics and the commonly known misclassified objects are mountain shadows or hill shadows which possess dark pixel that almost appear similar to a water body and often get misclassified and results in a false positive result. The problem of misclassification can thus be minimized by selecting appropriate threshold which would be then able to discriminate between different objects based on their precise spectral response to a greater extent. The methods which are working well for the cryospheric environment for feature extraction or land-cover classification does not really guarantee that they will be working in the same manner for the urban environment. Thus, in coming years it is expected that much of the work will be done on object-based approach or hybrid approach involving both pixel-based as well as object-based technology, with respect to lake feature extraction and a more accurate, versatile and robust method will be developed that would work independent of location (for both urban and cryosphere, single method would be able to extract water bodies accurately) and feature (for extraction of different types of lake a single method would be able to work). And also in coming years, super high spatial and temporal resolution optical satellites will be active which will yield even micro details of a region.

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