# Water Detection in an Open Environment: A Comprehensive Review

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**Summary**
Open surface water body extraction is gaining popularity in recent years due to its versatile applications. Multiple techniques are used for water detection based on applications. Different applications of Radar as LADAR, Ground-penetrating, synthetic aperture, and sounding radars are used to detect water. Shortwave infrared, thermal, optical, and multi-spectral sensors are widely used to detect water bodies. A stereo camera is another way to detect water and different methods are applied to the images of stereo cameras such as deep learning, machine learning, polarization, color variations, and descriptors are used to segment water and no water areas. The Satellite is also used at a high level to get water imagery and the captured imagery is processed using various methods such as features extraction, thresholding, entropy-based, and machine learning to find water on the surface. In this paper, we have summarized all the available methods to detect water areas. The main focus of this survey is on water detection especially in small patches or in small areas. The second aim of this survey is to detect water hazards for unmanned vehicles and off-sure navigation.
***Keywords:***
*Water detection, Radars, Sensors, Stereo cameras., Satellite.*

## 1. Introduction

In the era of autonomous vehicles and many other applications of water, the detection of water in the outdoor environment becomes more important. Water hazards may be in different shapes, types, and environments. The detection of water may be categorized on the basis of applications. Water hazards are detected for autonomous vehicles [1], Water reservoirs, and monitoring for agriculture and other purposes [2]. Water detection for special purposes like dengue larvae detection [3] is also important. Water hazards in the case of unmanned vehicles are ponds, mud, puddles, streams, river, and lakes. Water hurdles may be in different shapes, densities, and brightness levels based on daylight or shady areas. Water hazards create problems for autonomous vehicles and cause detract from the path or mislead to wrong decisions [4][5]. To avoid hurdles and problems from water patches on road it is necessary to detect water areas well before time. There are two basic classifications of water detection, active water detection, and passive water detection. In active water detection, Radars and Sensors are used to detect water at an open surface or under the surface. In passive water detection, stereo cameras, and satellite images are used to segment water and no-water area. To detect water areas, sensors [6][7][8], near-infrared [9][10], infrared thermometers [11], and stereo vision based [12][13] methods are used.

It is a need for time to detect water resources for better management. Different methods are used to detect the water resources such as satellite imaginary monitoring [14], and Synthetic Aperture Radar [15][16]. Detection of unseen water resources plays a vital role in water management and utilization, especially in the shortage of water.

Water detection for a special purpose or at a small scale is used for various applications. Dengue mosquitoes lay their eggs in fresh water and dengue larvae grow in freshwater [17][18][19]. To detect dengue larvae, it is important to detect the water areas where mosquito eggs or larvae are available. This is a gray area, there is no such research available for water detection for such applications. all the available research on water detection is available for unmanned vehicles and other purposes. Water detection in drums, water reservoirs, buckets, flower vases, earthen pots, tires, plastic bowls, plastic sheets, glass, a group of metal, discarded appliances, dust carries, bins, and ant guard's trays is still a gray area.

### 1.1 Related Reviews

Water detection is always taken as application-specific and some review articles are available on this topic. A review article [20] discusses four categories to find underground water tables such as reflected wave velocity, transmitted wave velocity between the wholes from the surface reflection coefficient, and ground wave velocity. In [21], the review of Thermal Infrared (TIR) for remote sensing focused on crop water stress is discussed. In [22], a review of surface water detection and delineation using remote sensing is discussed. In [23], a review of water bodies, and extraction in satellite images are discussed. In [24][25], a survey of outdoor water, hazards is investigated. By using infrared imagery, it is observed that the absorption coefficient of water is higher when compared to the visible range. In [26], thresholding techniques are reviewed for water detection.

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## 2. Water Detection Methods

Water detection in the outdoor environment is mainly classified into two major areas. The details are shown in Fig. 1.

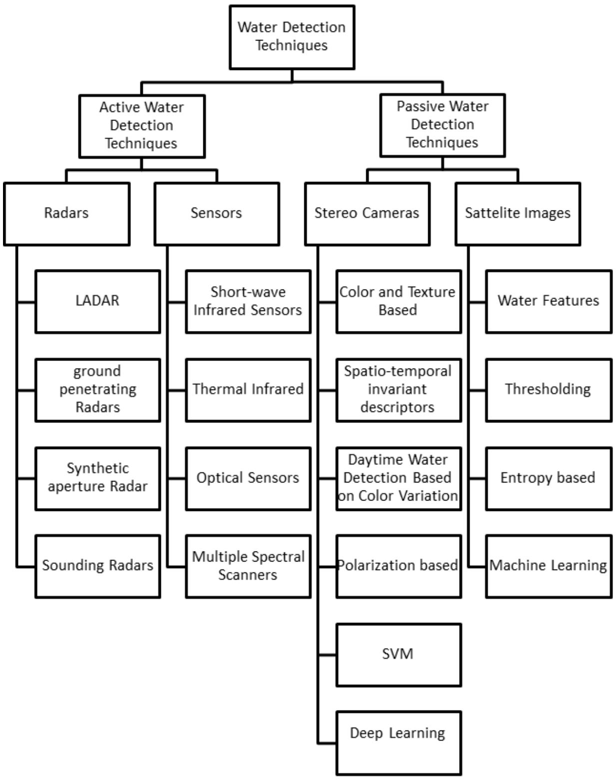


Fig. 1:Water detection techniques

Active water detection techniques and passive water detection techniques. In active detection techniques, laser systems are employed to detect wet areas. In this technique, different radars and sensors are implemented for water forecast or detection. A laser beam is transmitted, that beam reflects from different surfaces and is received at the receiver of the laser or radar. The received beam has different reflections from different surfaces. The receiver decides on the wet areas on the basis of reflected rays. In the second form of water detection which is passive, different cameras are used. The received images are segmented by any available technique. Stereo cameras, satellite images, and other techniques related to imagery are used for water detection or wet area detection. Multiple image segmentation methods are available to detect water & no water. Water can be classified by using image processing, machine learning, and deep learning techniques. The available literature on water detection techniques is discussed below.

### 2.1 Radar-based water detection

Radar is commonly used for water detection in open environments. Multiple radars are placed to detect water or wet areas. Radar transmits electromagnetic waves and these waves are reflected back from the water bodies that are received at the receiver. The parameters of the received waves tell the amount of water. Water detection with radar is further categorized into sub-types.

#### 2.1.1 LADAR as RADAR

In [27], LADAR, color cameras, and polarization-based sensors are used to detect the water. The LADAR hits are converted to build the color image space and data points are overlaid to show the color image segmentation as water and no water areas. In [28], the detection of obstacles, and the detection in foliage using LADAR and Radar are discussed. An algorithm is presented which detects obstacles in tall grass with single-axis LADAR. The discussed model shows that LADAR can penetrate from 10cm to several meters. LADAR results generate a high-resolution 2-D map. In [29], boundary detection and tracking using LADAR are discussed. An extended Kalman filtering using 2-dimensional LADAR is used to detect the boundaries of the road. The same method can be used for water area and no water area boundary classification. The above technique is simpler and more efficient. In [25], the detection of water hazards for autonomous off-road navigation is discussed to measure surface reflections and beam attenuation from a water body using LADAR. It covers the different angles and distances to prove the water detection. The authors also discussed that the depth of the water can also be determined by using LADAR.

#### 2.1.2 Ground-penetrating Radar (GPR)

In [30], the concept of GPR is discussed. This method is good for underground water detection however it has limitations in detecting water on the open surface level. In [31], the authors dis- cussed the measurement of soil water content using ground-penetrating radars. Soil water content can be measured by quantitative soil water content detection and hydrological parameter estimation using GPR. To achieve good accuracy, GPR requires sufficient and spatially continuous surface disparity in dielectric permittivity. In [32], the main focus is on accurate measurements of the different techniques to locate water content. The accuracy of time-domain reflectometry (TDR), wide-angle reflection and refraction (WARR), and single trace analysis (STA) were determined from aggregate water content and refractive index. It is concluded that the accuracy of TDR and WARR is the same while the accuracy of STA is a little low as compared to the other two methods.

In [33], underlying the physical mechanism of GPR for underground water detection is addressed and synthetic modeling is used for real data analysis.

#### 2.1.3 Synthetic Aperture Radar (SAR)

In [34], the volume variation of Lake, Izabel water is discussed. An Advanced SAR (ASAR) is used to collect inundated area variation. Image processing techniques are used to make estimations for the inundated areas. In [35][36], SAR images are used to find the flood area and the segmentation of water and no water area. SAR images are filtered and corrected geometrically, after that a threshold technique is applied to segment water and no water area. SAR performs better in a hazy atmosphere, fog, smog, low visibility, and light rain. In [37], a new semi-automated surface water detection method using SAR is discussed. This method works using a combination of radiometric thresholding and image segmentation by linear iterative clustering superpixel algorithm. In [38], a new method is discussed in which SAR images are calibrated to 1x1 degree tiles. A probability density function is calculated for each tile for water vs no water and finally, a training data set is established.

#### 2.1.4 Sounding Radars

The sounding RADAR is an application of a RADAR. The radio echo technique is used to find subsurface layers on the ground surface layer. In [39][40], the electrical and magnetic properties of a Martian surface and subsurface are discussed. In [41], local geoelectrical methods are used to find the underground water. It is investigated that the geoelectrical properties of Martian layers are not unique. In [42], the distribution of basal water between Antarctic subglacial lakes is also discussed.

### 2.2 Sensors-based water detection

Sensors-based water detection is normally used for small distances. Every sensor did not perform well in all conditions, the application of each sensor is different & accuracy depends on local conditions.

#### 2.2.1 Shortwave Infrared Sensors

In [24], a survey of outdoor water, hazards is investigated. In [25], water hazard for autonomous vehicles is discussed. Water bodies are shown dark in near-infrared, overhead imagery. Ice and snow have very strong absorption beyond 1.4 µm and the wavelength about 1.5 and 1.6 µm is used to detect water, ice, and snow. In [43], a linear physical-based model is applied using shortwave infrared (SWIR) sensors to detect moisture. The proposed model works in the solar domain (350-2500 nm) and is based on Kubelka–Munk two-flux radiated transfer theory. In [44], SWIR is used with normalized difference water index (NDWI) and moisture stress index (MSI). It is concluded that Satellite images with the data of SWIR are compared and show that MSI is less suitable for quantifying soil moisture. In [45], quantitative analysis of moisture in a solar module using SWIR is discussed. The concept of water reflectometry detection (WaRD) by using SWIR is implemented to calculate the water content on solar cells. In [46], quantitative analysis of water content is carried out by applying pixel-to-pixel data to moderate resolution imaging spectroradiometer and it shows good results.

#### 2.2.2 Thermal Infrared Sensors

Thermal infrared sensors are commonly used in agriculture to detect water content, moisture, and water utilization by crops and plants. In [47], ground-based handheld thermal imagery is used to detect groundwater springs at a beach. The IR cameras were installed at an incident angle vertically to the ground surface. The limitation of this method is that it works purely in winter or summer. it did not perform well in moderate weather. In [48], thermal infrared imagery is used to detect canal water leakage detection. Thermal imagery in the range of 8-14 µm of the electromagnetic spectrum was found best to detect leakage sites. In [49], an unmanned air-borne vehicle with TIR is used to detect the irrigation effect on cotton crops. The TIR of 7-14 µm is used with an altitude of 90 degrees and 0.5 spatial resolution. The limitation of this method is the impact of bare soil contributions during low canopy cover. In [50], groundwater discharge detection TIR is discussed. Most of the applications of TIR are agriculture-based and small water content detection.

#### 2.2.3 Optical Sensors

There are three types of optical sensors i.e., coarse spatial sensors, medium spatial sensors, and high spatial sensors [51]. In coarse spatial resolution is used for flood inundation [52][53][54]. The NOAA and Advanced Very High-Resolution Radiometer (AVHRR) reduce efficiency from clouds. The Moderate-resolution Imaging Spectroradiometer (MODIS) was used regularly in 2000 and these Satellite-based sensors were widely used for atmosphere monitoring and surface water detection [55][56][57]. In medium spatial sensors, the spatial resolution is increased from 80m to 30m. Landsat-8 is the most recent satellite launched to detect sur- face water areas [58][59][60]. High spatial resolution sensors are able to provide resolution at meter level and sub-meter level that makes it possible to detect small bodies of water. The limitations of these methods are small scene coverage mapping for large water bodies, shadows on images [61], and revisit frequency of these sensors. These type of sensors shows high accuracy at the Kappa coefficient = 0.95 and with high resolution to detect small water bodies [62][63][64].

#### 2.2.4 Multiple Spectral Scanners

A normal sensor uses RGB wavelengths but multiple spectral sensors use RGB and other invisible wavelengths also. In [65], the authors highlight a Dempster-Shafer theory that is modeled with supervised learning and the spectral band of water properties in a fully unsupervised context. In [66], the concept of ZY-3 multi-spectral imagery is used for water bodies detection. In the first method, a new water index named the high-resolution water index (HRWI) is used to detect water bodies, and the result is compared with the Normalized Difference Water Index (NDWI) while in the second method, the automatic urban water extraction method (AUWEM) algorithm is used with NDWI1 and NDWI2. Both methods show high accuracy, stability, and robustness in different environments and conditions. The limitations of both methods are complex and less efficient compared to NDWI.

### 2.3 Stereo Camera-based Water Detection

The stereo cameras are used as input devices to capture video and images containing water areas.

#### 2.3.1 Color & Texture based detection

Water detection based on color and texture features [67], is a passive technique. By comparing the single feature method, it is more robust to the variation of ambient light. In [68], color and texture, both are used for water classification. For color, brightness values in HSV color space are combined with texture detection based on the local properties of the shape for segmentation. Finally, the variance of the local binary pattern is used to formulate the result. In [69], water is detected in multiple video frames. It used the measurements of entropy of trajectories of optical flow in different frames. The limitation of this method is camera resolution and propagating labels which may lead to improper dynamic texture analysis.

#### 2.3.2 Spatio-temporal invariant descriptors

In [70], the motion properties of the water are explored. This method is robust in nature and per- form well with high classification accuracy. The limitation of descriptors is that they required dense sampling which leads to a large number of features which is difficult to handle [71]. In [72], a simple random forest model is applied to eleven different feature variables of remote sensing data. This method is simple, with high accuracy to detect water areas. In [73], remotely sensed data is used to a mapping of spatial and temporal variations of water inundation are observed. In [74], the combination of remote sensing and GIS is used to measure the quality of water over spatial and temporal scales.

#### 2.3.3 Daytime Water Detection Based on Color Variation

In [6][7], color variations-based techniques are used to segment water areas in the daytime. In [75], the sky-reflected colored imagery is used to classify the water area. The RGB imagery has different color variations for water and other terrains. It performs well for mid and far ranges and has the limitation of close range and small water bodies. In [76], the evaluation of water-detecting methods for unmanned vehicles is discussed. In [77], a color- tune-able lanthanide and radiometric sensors are used to detect water in ethanol.

#### 2.3.4 Polarization-Based Water Detection

In [78], water area can be separated by comparison of polarization degree and similarities between water phases. In [79], a single pixel is identified in underwater imagery. Two cross-polarization schemes eliminate the background which is due to water and this scattered pixel is reconstructed by a cross-polarization method. In [80], a new technique is developed to detect water bodies for applying the traps to avoid chironomid females from laying eggs in water reservoirs. In [81], a polarization scheme is used to remove image degradation effects from underwater imagery.

#### 2.3.5 Support Vector Machine (SVM)

In [82], to detect the water or wet areas, SVM is used for hypothesis verification. Polarization difference, gradient magnitude, and graininess features are used for classification. In [83], wet and dry metals were classified using SVM. In [84][85], water leakage from the pipe using SVM is discussed. In [86], to forecast the dam water level, SVM is compared with an adaptive neuro-fuzzy inference system. In [87], decision trees and SVM are used for anomaly detection in the water distribution network. It shows that linear SVM is good for water quality monitoring. In [88], a least square SVM is used for water stress classification. In [89], wet road surface identification using SVM is discussed. The result shows that polynomial and RBF kernels did not perform well but linear kernel shows good results. In [90], super-pixel segmentation and SVM are used for the detection of water channel damage slope.

#### 2.3.6 Water detection using Deep Learning and stereo camera

A deep learning approach is an effective method for water detection in specific applications. In [91][92], Small-World Neural Network (SWNet) is used to classify wet or water area. SWNet shows high accuracy by reusing pooling indicts and by choosing a lightweight decoder. In [93][94][95], water hazard detection with a fully convolutional neural network (CNN) based on reflection attention units is discussed. Here, focal loss and distance between one pixel and an average of 2 columns are calculated. In [96][97], a multi-scale CNN is used for water classification. In [98], an Artificial neural network is used to generate a navigation map and principal component analysis for comparison of extracted information for water detection. In [99], a CNN is applied in the smart near-infrared analysis of water pollution for agriculture.

## 2.4 Satellite Images based Water Detection

Satellite-based images are used for large-scale water identification and classification. Satellite data is largely used for the calculation of surface-covered water areas, seashore monitoring, and flood mapping in big disasters.

### 2.4.1 Water Features

In [100], different water features like the Normalized Difference Water Index (NDWI) modified normalized difference water index (MNDWI), Water ratio index (WRI), Normalized difference moisture index (MDMI), vegetation index, and automatic water extraction index (AW) are used to segment the water area and change in water area. In [101], the automatic water extraction index (AWEI) with the google earth engine, and in [102], the water natural difference index (NDWI) is used for water detection. In [103], constrained energy minimization is used with MNDWI and AWEI for water segmentation.

### 2.4.2 Thresholding

Water detection for open surfaces has many thresholding techniques These methods are Huang and Wang's Fuzzy [104], Inter-mode [105], Iso-data [106], Maximum [107], Mean [108], Renyi's [109], and Minimum Error [110]. All the above techniques were applied in satellite images for water detection. It shows that minimum thresholding techniques were the best technique for water body extraction and percentile, shan-bag has the lowest accuracy for water detection.

### 2.4.3 Entropy-based

High-resolution images obtained by satellites are used for water detection. In [111], an entropy-based method is used for water area segmentation. In this scheme, Kapur's entropy-based thresholding method is used to formulate quality and performance matrices. In [112], entropy-based fusion indices and DSM, derivatives are for water sur- face extraction. In [113], entropy-based assessment and clustering of water areas are discussed and in [114], entropy-based water leakage detection is discussed. The authors in [115] focused on the Entropy-Based Naıve Bayes method for flood hazard evaluation.

### 2.4.4 Machine Learning

#### 2.4.4.1 Ensemble Classification

In [116], an ensemble classification method is used for water detection in satellite images. Three classifiers are used Maximum likelihood, SVM, and Random Forest. Ensemble classification is also used for different applications of water detection in satellite images [117][118]. In [119], a collaborated decision-making (CDWI) with water indices instead of threshold single water index (WI) is compared. The CDWI is more accurate in comparison to other models.

#### 2.4.4.2 Support Vector Machine (SVM)

The SVM is largely used for pipeline leakage detection as well as water area segmentation in satellite images [120][121][122]. In [123], SVM is used for river mapping in a satellite image. SVM is used to detect water level changes in a dam [86].

#### 2.4.4.3 Bayesian

In [124], the Bayesian procedure is used to improve the results of NDWI in satellite imagery. The climate change water resources uncertainties are discussed in [125], and in [126] anomalies in unlabeled water using Bayesian are elaborated. Water leakage and anomalies in water networks are explained in [127]. There are many methods available for open surface water extraction but most are application-specific and produce different results in different applications.

## 3. Conclusion

Water detection in open surfaces in the presence of different textures, backgrounds, and light conditions is a difficult task. A lot of work has been done in remote sensing and satellite imagery that is used for many applications such as Flood area monitoring, off-sure surveillance, water hazard detection, and water reservoir monitoring.

Radars are used according to applications such as LADAR, ground-penetrating Radars, Synthetic aperture Radars, and Sounding Radars. LADAR creates a 2-D map on the result of reflections. To achieve good accuracy, ground-penetrating radars require sufficient and spatially continuous surface disparity in dielectric permittivity. An advanced synthetic aperture radar is used to collect inundated area variations. The sounding RADAR uses a radio echo technique to find subsurface layers on the ground surface layer. For water detection, dielectric properties are calculated that differ from the dry and wet surfaces. The comparison shows that a single Radar did not give accurate segmentation as a group of Radars at different angles and heights produce accurate water area segmentation.

Different types of Radars are useful for different applications.

Sensors are used for under-surface water detection and open-surface water detection. Short-wave, Thermal, Optical, and Multi-spectral sensors and applied for different applications. By using infrared imagery, it is observed that the absorption coefficient of water is higher when compared to the visible range. The SWIR cameras within wavelength sensitivity of 0.9 to 1.7 micrometers produce good results. Incident angle plays a vital role in the accuracy of water body detection. Thermal sensors are used for agriculture purposes to detect soil moisture for irrigation. Remote sensing is the most suite able way to find surface water. A normal sensor uses RGB wavelengths but multiple spectral sensors use RGB and other invisible wavelengths also. The study concludes that sensors can map 1-D and 2-D results of water bodies and can accurately measure the dimensions and depth of a water area. The accuracy depends upon the angle and wavelength selected for a specific area. Stereo cameras capture the images and the water area is segmented into captured images or videos. Different color variations, features, and luminance factors are used to distinguish between water and no water area. This type of water detection may be disturbed by shadows, texture, and brightness issues. In this method, the brightness of reflections, the ratio of saturation, and GLCM extracted feature sets are used to form a five-value feature set. The descriptors and Spatio-temporal Markov random field is used to detect the water mask in specific applications. The color change in the term of brightness is used to distinguish starting and ending points of the water body. Machine learning and deep learning play a vital role in image segmentation and classification.

Satellites are widely used for remote sensing, high-level water area segmentation, seashore monitoring, and flood mapping in big disasters. There are different orbits and image locations to capture satellite images. This type of water detection could not detect small areas of water bodies. Different techniques are applied to satellite images for water area identification such as water features, thresholding, entropy-based, machine learning, and deep learning. A better image classification technique can produce better results.

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