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Title

Remote sensing and avian influenza: a review of image processing methods for extracting key variables to determine avian influenza virus survival in water from Earth Observation satellites

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Abstract

Recent studies have highlighted the potential role of water in the transmission of Avian Influenza (AI) viruses and the existence of often interacting parameters that determine the survival rate of these viruses in water; the two main variables are temperature and salinity.

Remote sensing has been used to map and monitor water bodies for several decades. In this paper, we review satellite image analysis methods used for water detection and characterization, focusing on the main variables that influence AI virus survival in water.

Optical and radar imagery are useful for detecting water bodies at different spatial and temporal scales. Methods to monitor the temperature of large water surfaces are also available. Current methods for estimating other relevant water variables such as salinity, pH, turbidity and water depth are not presently considered to be effective.

Keywords

Remote sensing, water, avian influenza, H5N1 virus
Introduction

Avian influenza (AI) is a viral infection of birds that occurs worldwide. Depending on their level of virulence to chickens, avian influenza viruses are divided into two groups, low-pathogenicity avian influenza (LPAI) viruses and high-pathogenicity avian influenza (HPAI) viruses (Alexander, 2000). Among them, the Asian HPAI H5N1 virus is the cause of extreme losses in the poultry sector, since 2003 an average of 200 millions of birds died of the disease or have been culled to control its spread, global loss for control, vaccination and biosecurity was estimated in billions of US Dollars (Otte et al., 2008). And at the same time this virus is of greatest concern for human health with regard to its potential to become the next pandemic strain (FAO, 2007; WHO, 2006). Identified for the first time in 1996 in China, the virus had spread unrelentingly over South Asia since 2003, progressing westward from the end of 2005 into Eurasia and then over Europe, to finally reach Africa at the beginning of 2006 (FAO, 2007). Currently, the number of human cases around the world has reached 403, among which there have been 254 deaths (as of 27 January 2009) (WHO, 2009). This crisis not only represents an important threat for human health, but it also represents many socio-economic problems involved in the agriculture and poultry industries. Despite enforced sanitary measures, some countries (particularly in South East Asia) remain subject to periodic recurrences of the virus and thus require new strategies to be implemented. In particular, to improve disease surveillance, we need to have a better grasp on the ecology of the virus, especially with respect to factors that favor the resurgence of new cases.

Several species of wild birds and poultry (notably ducks for the H5N1) have been identified as reservoirs for avian influenza viruses (AIV) (FAO, 2007). The disease can be transmitted either by direct contact with an infected host or indirectly through exposure to materials contaminated with infected feces or respiratory secretions. Several experimental works have been done to determine the environmental factors that influence the persistence of AIV in
feces. Beard et al. (1984) established that the virus could survive up to 35 days in wet feces kept in closed vial at 4°C but this survival time will drop to 2 days if stored at 25°C. At ambient temperature the survival of AIV virus in chicken manure was evaluated at 6 days (Lu, 2003). The direct exposition of fecal material to UV light doesn’t have an impact on viral infectivity (Chumpolbanchorn et al., 2006).

Transmission of AIV within wild bird communities via the ingestion of feces-contaminated water is well documented (Brown et al., 2007). In late 70s, early 80s, wide varieties of AIV were isolated from unconcentrated water from 6 lakes in Canada (Hinshaw et al., 1979), lakes in United States (Halvorson et al., 1983) or from water ponds from duck farms in Hong Kong (Markwell and Shortridge, 1982), showing that contaminated water supplies can constitute a reservoir maintaining the virus in the environment and be a source for the contamination of wild birds or other animal species.

This hypothesis is supported by several studies showing that the viruses are able to survive in water for longer or shorter time periods depending on environmental characteristics (Brown et al., 2008; Brown et al., 2007; Stallknecht et al., 1990; Weber and Stilianakis, 2008; WHO, 2007; Zarkov, 2006). Using this virus characteristic, researchers in Hong-Kong proposed some surveillance strategy on live-birds market by sampling drinking water taken from poultry cage, showing that the virus could survive between 8 to 24h in this environment depending on level of chlorination and organic content of the water (Leung et al., 2007).

Recently a large diversity of AIV was detected in sediments of ponds in Alaska, hosting a wide number of migratory waterfowl. Even if the study didn’t show the viability of the virus in this condition they indicated that these sediments could play important role as year-to-year reservoir (Lang et al., 2008).

Late work on mathematical model to simulate the transmission and the maintenance of AIV in wild birds communities have shown that persistence of AIV in aquatic ecosystems is a key
parameters in the dynamics of infection in bird communities (Breban et al., 2009; Roche et al., 2009). These results are underlying the importance to develop new methodologies to identify potential risk areas of aquatic transmission.

Remote sensing technologies, which allow the mapping of environmental variables, have been used in different epidemiologic studies (reviews by (Curran et al., 2000; Hay et al., 1997; Herbreteau et al., 2007; Kalluri et al., 2007)).

So far, remote sensing has been rarely used in the context of avian influenza. Few studies are available that include the extraction of agricultural indicators (Gilbert et al., 2007; Gilbert et al., 2008) or environmental indicators like surface temperature (Guo et al., 2005; Xiao et al., 2007). Gilbert et al. (2007) highlighted the strong association between intensive rice cropping areas and the abundance of free-grazing ducks, using data from the Moderate Resolution Imaging Spectroradiometer (MODIS). The latter appears to be a significant factor in the transmission and persistence of H5N1 in Thailand (Gilbert et al., 2006). Land surface temperatures derived from MODIS thermal imagery were used by Xiao et al. (2007) to delineate the traveling wave of frost that triggers bird migration in the western Palearctic region and thus impacts the H5N1 HPAI spread and seasonal dynamics.

All of these studies concern the detection of indicators for the presence of hosts (poultry or wild birds) as risk factors for H5N1 HPAI transmission. At this point, no study exists to our knowledge that deals directly with the detection of water as a potential survival environment for the H5N1 virus and/or as place of risk for virus transmission.

The objective of this paper is to review the potential contributions of remotely-sensed data and image analysis methods for identifying water bodies and inundated areas and their classifications according to various key variables, to define AI-related health risk indicators.

After presenting the key factors known to influence the AI virus survival in water, a review is given of what could legitimately be expected from various sensors (Synthetic Aperture Radar
(SAR), thermal and optical) onboard present and forthcoming Earth Observation satellites, in
terms of their mapping capabilities for water surfaces and related characteristics that influence
virus persistence.

1. Environmental factors influencing the survival of AI viruses in water

Fecal-oral transmission by contaminated water is a recognized mechanism of AI virus
transmission (Brown et al., 2007). This has spurred interest in the parameters affecting the
survival of AI viruses in water. Because little is known about the persistence of subtype HPAI
H5N1 virus in the environment, we review the environmental factors influencing the survival
of both lowly pathogenic as well as highly pathogenic avian influenza viruses, given that
under the same conditions HPAI H5N1 viruses seem to have reduced fitness in water
compared to LPAI, as suggested by recent works on AI virus inactivation in water (Brown et
al., 2008; Brown et al., 2007; Weber and Stilianakis, 2008).

Temperature. Experimental studies on LPAI (Brown et al., 2008; Brown et al., 2007;
Stallknecht et al., 1990; Webster et al., 1978) as well as HPAI (Brown et al., 2007; Phuong,
2005) viruses indicate that temperature is a key factor for virus survival; the persistence of the
virus in water is strongly reduced by high temperatures. For example, Brown et al. (2007)
estimated that the time required for an initial H5N1 viral concentration in distilled water to be
reduced by 90% was between 16 and 26 days at 17 °C and between 4 and 5 days at 28 °C.

Salinity. In the same study (Brown et al., 2007), three salinity levels were also used. It was
shown that higher water salinity could reduce virus survival, and that the effect of salinity was
more prominent at lower temperatures. These results are consistent with previous studies on
LPAI viruses (Stallknecht et al., 1990; Zarkov, 2006). In a recent study, Brown et al. (2008)
showed that LPAI isolates have important individual variations in response to increases of
salinity in water. From their results, they concluded that some LPAI viruses will reach their
peak of infectivity in brackish water with salinity between 10,000 and 20,000 ppm.
pH. LPAI viruses were found to be stable within a pH range of 7 to 8.5 (Brown et al., 2008; Stallknecht et al., 1990). These results were confirmed by observations of the infectivity of LPAI viruses from different natural water types (Zarkov, 2006).

Turbidity. Very little quantitative information is available on the impact of water turbidity on the survival of AI viruses. According to Phuong et al. (2005), the H5N1 virus survives longer in water with organic material, but the presence of living microorganisms reduces the survival time of influenza viruses in water (Zarkov, 2006).

Overall, temperature and salinity seem to be the two key variables influencing HPAI virus survival in water. For instance, H5N1 can be expected to persist for several weeks in water with low salinity and low temperature (Weber and Stilianakis, 2008). In the next two sections, we review the capacity of remote sensing to (i) delineate water bodies and map flooded areas and (ii) extract those parameters influencing virus survival in water.

2. Mapping water bodies and flooded areas

Several methods are used in radar and optical remote sensing to delineate water bodies and map flooded areas. This review covers sensors with medium to very high spatial resolutions, which are compatible with the size of the water bodies of interest in the context of AI. Tables 1 and 2 summarize the characteristics of currently available optical and radar sensors to detect water bodies.

Open water detection. Within the visible (VIS) and infrared (IR) spectra, water can be characterized by a high reflectance in the blue wavelength, which rapidly diminishes in the visible wavelengths to become very weak in the near infrared (NIR). Based on this spectral signature, several indices were developed to delineate water bodies using ratios of spectral bands; the most frequent wavelengths used were NIR, Green (G) and Middle Infrared (MIR). These spectral indices aim to maximize the difference of pixel values between the object being studied (i.e., water bodies) and other surfaces. Table 3 summarizes the indices
encountered in scientific literature and indicates how they are calculated and in which context they were originally used.

The interaction between the radar wave and the surface of water is mainly affected by surface roughness and depends on instrument parameters such as radar wavelength, incidence angle and polarization. With SAR data in single polarization, it is possible to effectively detect open water (Smith, 1997), when using the appropriate configuration. Baghdadi et al. (2007) showed that the optimum configuration to discriminate water and land corresponds to SAR data acquired at a high incidence angle (>30°), independently of polarization (HH, HV, VH, VV) or to data acquired at a low incidence angle in cross-polarization (HV, VH), using ASAR/ENVISAT data (C-band).

Detection of flooded areas. In addition to open water areas, the detection of flooded areas with vegetation, like rice paddies, swamps or flooded forests, may be of interest in the context of AI as those areas may be at risk for the transmission of the virus and act as natural reservoirs for virus survival. In a recent study on environmental risk factors in Romania (Ward et al., 2008), the presence of flooded shrub or herbaceous land cover was highly associated with an increased risk of HPAI outbreaks in domestic poultry.

The use of optical remote sensing to map such flooded areas is limited when trees and floating vegetation screen the water surface (Smith, 1997). Thus, some methods were developed using optical sensors to monitor flooded areas, based mainly on time series analysis of multispectral images and most often through the study of the temporal dynamics of vegetation indices (Sakamoto et al., 2007; Xiao et al., 2005) or with land use change detection algorithms (Zhan et al., 2002).

In radar remote sensing, the use of multiple frequencies is interesting for identifying several types of inundated land (Smith, 1997). For example, Hess et al. (1995) showed that it was possible to map inundated areas and flooded vegetation in the Amazon Basin using C- and L-
bands SAR data. Baghdadi et al. (2001) used a decision tree based on the threshold of C-band backscatter values in different polarizations to discriminate wetlands. Time series SAR images were used in other studies to monitor flood dynamics (Martinez and Le Toan, 2007), and to identify rice crops (Chakraborty and Panigrahy, 2000; LeToan et al., 1997; Panigrahy et al., 1999; Shao et al., 2001) or marshes (Pope et al., 1997) through the analysis of changes in backscatter values.

Finally, some authors demonstrated the ability of optical and radar remote sensing data fusion to improve the classification of flooded land cover types (Castañeda and Ducrot, 2008; Oguro et al., 2001; Seiler et al., 2008).

Due to the double-bounce scattering between the water surface and the vertical stems and leaves of the vegetation, the radar returns from marshes or flooded vegetation are high and easily separable from other surface types (Baghdadi et al., 2001). However, the detection of flooded vegetation could be problematic if the vegetation cover is dense or if SAR data is acquired using low radar wavelengths (X or C-bands). The use of high radar wavelengths (L-band) allows the radar waves to penetrate the vegetation cover and reach the underlying water.

3. Water parameters assessment using remote sensing

The extraction of water parameters from satellite measurements has been the focus of numerous studies. In this review, we focus on the key variables influencing the AI virus survival in water as determined in section 2, i.e., temperature, salinity, pH and turbidity. We also include water depth estimation using remote sensing, as this factor may influence temperature.

**Temperature.** Water surface temperature can be estimated with remotely sensed thermal infrared (TIR) images (Anding and Kauth, 1970; Handcock et al., 2006; Kay et al., 2005; Li et al., 2001; Reinart and Reinhold, 2008; Schott et al., 2001; Wloczyk et al., 2006). Two
thermal bands are required to compensate atmospheric effects in an appropriate way (split-
window technique) (McMillin and Crosby, 1984). Nevertheless, studies using one TIR band
from Landsat Enhanced Thematic Mapper (ETM+) imagery showed satisfactory results
(Schott et al., 2001; Wloczyk et al., 2006). Thus, depending on the spatial resolution of the
sensor (see Table 1), the temperature of rivers, lakes and seas may be assessed with good
agreement between remote sensing-estimated and ground-measured temperatures. Most of the
studies concern the estimation of sea-surface temperatures (Anding and Kauth, 1970; Franca
and Cracknell, 1994; Li et al., 2001); examples of applications to land-surface water bodies
(of interest in the AI context) are scarce, in part because of difficulty detecting streams and
small lakes using satellite remote sensing (Kay et al., 2005). For example, Reinard and
Reinhold (2008) used MODIS data to map temperatures in large lakes and Handcock et al.
(2006) estimated that reliable satellite TIR measurements are limited to large rivers (about
180 m across). For smaller rivers and streams, only airborne thermal remote sensing may be
used (Torgersen et al., 2001).

Salinity. The potential of passive microwave remote sensing (L-band, 1.4 GHz) has been
described in several studies because the natural emission from water is modulated by salinity
in the decametric wave range (Blume et al., 1978; Kachan and Pimenov, 1997; Le Vine et al.,
1998; Singh et al., 1990; Wilson et al., 2001). Nevertheless, this is presently limited to
airborne remote sensing; the definition of a satellite sensor dedicated to the measure of sea
surface salinity is in process (Le Vine et al., 2004).

pH. The pH of water is one of the characteristics of water which may influence the survival of
avian influenza viruses in water (Brown et al., 2008; Stallknecht et al., 1990). Nevertheless, as
far as we know, there are no studies dealing with the estimation of water pH using remotely
sensed data, although Ferrari previously mentioned the influence of pH on the
**Turbidity.** Water turbidity is generally characterized by two main variables, the Chlorophyll-a concentration (Chl-a) (a measure of phytoplankton abundance) and the Suspended Sediment concentration (SS). These are key variables for assessing water quality. There is an abundance of scientific literature available on the assessment of these variables using optical remote sensing (Marcus and Fonstad, 2008). Indeed, turbidity is detected relative to water color, which can be characterized by reflectance values in the VIS and NIR spectra. Basically, Chl-a increases reflectance values in the Green and NIR wavelengths while SS increases those in the Red wavelengths (Seyhan and Dekker, 1986). Thus, empirical or semi-empirical models were developed to establish the relationships between in-situ turbidity measures and reflectance values or indices (band combinations). More sophisticated algorithms (e.g., neural networks, integrated approach using Geographic Information Systems) were also used to improve the quantitative predictive values (Chica-Olmo et al., 2004; Pozdnyakov et al., 2005). For example, Landsat Thematic Mapper (TM) and ETM+ or MODIS Terra images were used to assess turbidity in lakes (Giardino et al., 2001; Koponen et al., 2004; Wang et al., 2006), marshes (Bustamante et al., 2008), large rivers (Aranuvachapun and Walling, 1988; Mertes et al., 1993; Stech et al., 2007), reservoirs (Verdin, 1985), estuaries and coastal waters (Chen et al., 2007). The spatial resolution of the multispectral images setting limits the size of the water bodies that can be monitored.

In one of the few examples of literature available on the use of SAR data to assess water turbidity, Zhang et al. (2003) demonstrated that SAR was only marginally helpful for improving the estimation of turbidity, as derived from Landsat TM data.

**Water depth.** Bathymetry can be assessed by optical remote sensing techniques based on the relationship between water depth and water color, as light is attenuated through the water column. Different methods were developed to map the depth of shallow water bodies, taking into account that the signal measured by passive optical sensors is the result of interactions...
between depth, turbidity and the bottom reflectance (Bierwirth et al., 1993; Kumar et al., 1997; Lyzenga, 1981). Nevertheless, air-borne remote sensing systems are required for mapping depth in water bodies of small size (e.g. Leckie et al., 2005; Lejot et al., 2007; Lyon et al., 1992). Some other techniques using airborne remote sensing are also operational: stereophotogrammetry, ground penetrating radar and Lidar (Light detection and ranging) (see Feurer et al., 2008 for a review). On shallow seas, models assimilating radar images from the European Remote Sensing Satellite (ERS) and a first guess depth map were developed by Calkoen et al. (2001).

**Discussion**

Although scientific knowledge is still lacking on the global ecology of AI viruses in the natural environment, different studies support the essential role of contaminated water bodies, such as lakes and ponds, as environmental reservoirs of AI viruses. Moreover, flooded areas may play a role in the amplification of virus transmission, as they are often zones of contact between hosts (wild birds, domestic poultry). For these reasons, it seems important to be able to map and characterize the water bodies to define risk indicators for the study, surveillance and control of AI. The performances of Earth Observation Systems to achieve this goal were reviewed in this paper, highlighting the potential and the limits of remote sensing for identifying open water and flooded areas and the water parameters of importance for AI viruses, i.e., temperature, salinity, pH, turbidity and water depth.

Both optical and radar imagery are effective for detecting water bodies. Despite the important and frequent cloud cover in these regions, radar images seem particularly well-suited for mapping flooded areas in tropical ecosystems, due to the ability of radar systems to acquire information (Hess et al., 1995; Martinez and Le Toan, 2007).

Nevertheless, according to scientific literature, the characterization of the main water variables seems to be a difficult task. Algorithms for estimating water-surface temperatures
from TIR sensors are effective only for large water surfaces (seas, lakes, large rivers). For instance, SST and LST maps derived from MODIS data are produced and distributed routinely (USGS, 2008). Water salinity could be measured using passive microwave remote sensing, but these techniques are not yet operational. We did not find any studies concerning the use of remote sensing to estimate the pH of water, whereas this variable may be of importance for AI survival in water. There is abundant literature available on the assessment of turbidity from space, based on the relationship between water color and Chl-a or SS concentrations. Nevertheless, a calibration phase with in-situ measurements is required when applying the methods to a new area. Finally, several attempts to map water depth have been reported in the literature, but good agreement is obtained only in relative values, and it remains difficult to obtain water depth accurately.

Most of the methods listed here are well-suited for large water surfaces, due to the spatial resolution of the satellite imagery. Smaller water bodies like household ponds or small lakes are also of great interest in the study of AI virus survival; in Cambodia, bathing in these types of water bodies may be a risk factor for H5N1 HPAI transmission to humans (Vong et al., 2009). Instead, high or very high spatial resolution imagery should be used. However, the adaptation of the methods to very high spatial resolution data may not always be possible, due to the lack of appropriate wavebands and revisit characteristics.

In this review, we focused on the detection and characterization of water bodies, using Earth Observation Systems, as there is some evidence for their role as reservoirs of AI virus when contaminated (Brown et al., 2007; Weber and Stilianakis, 2008; WHO, 2007). In the future, the capacity of remote sensing to map other AI relevant variables (soil moisture, texture, vegetation cover, etc.) should be addressed, given that the knowledge of the ecology of AI viruses in the natural environment indicates a link between AI risk and factors like the characteristics of soils, vegetation, etc., which can be monitored using remotely sensed data.
Indeed, numerous others potential factors, like microflora, metal oxides, dissolved oxygen, UV radiation, etc., affecting AI persistence in water are currently investigated (IRD, 2007; European Commission, 2007).

In conclusion, remote sensing images can be used to map open water surfaces and flooded areas and to derive a limited number of water parameters: temperature, turbidity and water depth (the latter in relative values). In-situ measurements and/or additional modeling approaches are required to assess others key parameters for virus survival such as pH or salinity. Nevertheless, such preliminary approaches, as are currently available, can provide the first classification of zones for potential AI virus survival in the water of a given area. To help identify and map risk areas for AI, this information can be combined with other geographic layers concerning the poultry trade, such as the density and structure of poultry farming, migratory zones of wild birds, etc., using a Geographic Information System approach.
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Tables

Table 1. Characteristics of current optical sensors
Table 2. Characteristics of current SAR sensors
Table 3. Spectral indices used for water detection
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Table 1. Characteristics of current optical sensors

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>Spectral resolution (µm) [number and detail of bands*]</th>
<th>Pixel size**</th>
<th>Revisit period</th>
<th>Swath width</th>
</tr>
</thead>
<tbody>
<tr>
<td>Envisat</td>
<td>MERIS</td>
<td>0.39 - 1.04 [15]</td>
<td>Ocean: 1040 m x 1200 m; Land: 260 m x 300 m</td>
<td>1 – 3 days</td>
<td>1150 km</td>
</tr>
<tr>
<td>Terra</td>
<td>MODIS</td>
<td>0.4 - 14.4 [VIS: 11; NIR: 6; SWIR: 3; MWIR: 6; TIR: 10]</td>
<td>2 bands: 250 m (R, NIR); 5 bands: 500 m (VNIR); 29 bands: 1 km</td>
<td>1 – 2 days</td>
<td>2330 km</td>
</tr>
<tr>
<td>Terra</td>
<td>ASTER</td>
<td>0.52 – 11.65 [VIS: 2; NIR: 1; SWIR: 6; TIR: 5]</td>
<td>15 m (VNIR); 30 m (SWIR); 90 m (TIR)</td>
<td>16 days</td>
<td>60 km</td>
</tr>
<tr>
<td>Landsat 5 / 7</td>
<td>TM / ETM+</td>
<td>0.45 – 12.5 [NVIS: 4; SWIR: 2; TIR: 1]</td>
<td>30 m (NVIS, SWIR); 60/120 m (TIR ETM+/TM)</td>
<td>16 days</td>
<td>180 km</td>
</tr>
<tr>
<td>Landsat 7</td>
<td>ETM+</td>
<td>PAN: 0.52 - 0.90</td>
<td>15 m</td>
<td>16 days</td>
<td>180 km</td>
</tr>
<tr>
<td>EO-1</td>
<td>ALI</td>
<td>PAN: 0.48 - 0.69</td>
<td>10 m</td>
<td>16 days</td>
<td>37 km</td>
</tr>
<tr>
<td>EO-1</td>
<td>Hyperion</td>
<td>0.4 - 2.5 µm [220]</td>
<td>30 m</td>
<td>16 days</td>
<td>7.7 km</td>
</tr>
<tr>
<td>IRS-1C, 1D</td>
<td>WIFS</td>
<td>0.62 - 0.86 [R, NIR]</td>
<td>188 m</td>
<td>5 days</td>
<td>806 km</td>
</tr>
<tr>
<td>IRS-1C, 1D</td>
<td>LISS-3</td>
<td>0.52 – 0.86 [VIS: 2; NIR: 1]</td>
<td>23 m</td>
<td>24-25 days</td>
<td>140 km</td>
</tr>
<tr>
<td>IRS-1C, 1D</td>
<td>PAN</td>
<td>PAN: 0.5 - 0.75</td>
<td>5.8 m</td>
<td>24-25 days</td>
<td>70 km</td>
</tr>
<tr>
<td>SPOT 4</td>
<td>HRVIR</td>
<td>0.5 – 1.75 [VIS: 3; SWIR: 1]</td>
<td>20 m</td>
<td>26 days</td>
<td>60 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PAN: 0.61 - 0.68</td>
<td>10 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPOT 5</td>
<td>HRG</td>
<td>0.5 µm – 1.75 [G, R, NIR, SWIR]</td>
<td>10 m (VIS); 20 m (SWIR)</td>
<td>26 days</td>
<td>60 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PAN: 0.51 - 0.73</td>
<td>5 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ikonos</td>
<td></td>
<td>0.45 - 0.9 [VIS: 3; NIR: 1]</td>
<td>3.2 m</td>
<td>3 *** days</td>
<td>11 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PAN: 0.49 - 0.90</td>
<td>0.82 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quickbird</td>
<td></td>
<td>0.45 - 0.90 [B, G, R, NIR]</td>
<td>2.44 m</td>
<td>3 *** days</td>
<td>16.5 km</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PAN: 0.45 - 0.90</td>
<td>0.61 m</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
*VIS: Visible; NIR: Near infrared; VNIR: Visible and Near Infrared; SWIR: Short Wave Infrared; MWIR: Middle Wave Infrared; TIR: Thermal Infrared; PAN: Panchromatic; B: Blue, G: Green, R: Red

** Medium, High and Very High spatial resolution data correspond to > 100 m, 10-100 m and < 10 m pixel size respectively

*** off-nadir
## Table 2. Characteristics of current SAR sensors

<table>
<thead>
<tr>
<th>Satellite and sensor</th>
<th>Band</th>
<th>Incidence</th>
<th>Polarization</th>
<th>Spatial resolution</th>
<th>Revisit period</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERS-2</td>
<td>C</td>
<td>23°</td>
<td>VV</td>
<td>12.5 m</td>
<td>35 days</td>
</tr>
<tr>
<td>RADARSAT-1</td>
<td>C</td>
<td>20°-50°</td>
<td>HH</td>
<td>6.25 to 50 m</td>
<td>24 days</td>
</tr>
<tr>
<td>RADARSAT-2</td>
<td>C</td>
<td>20°-60°</td>
<td>HH,HV,VH, VV</td>
<td>3 to 100 m</td>
<td>&lt; week</td>
</tr>
<tr>
<td>ENVISAT-ASAR</td>
<td>C</td>
<td>15°-45°</td>
<td>HH or VV or HH/HV or VH/VV or HH/VV</td>
<td>12.5 to 75 m</td>
<td>&lt; week</td>
</tr>
<tr>
<td>ALOS/PALSAR (3 modes:</td>
<td>L</td>
<td>20°-60°</td>
<td>HH or HH/HV or HH/HV/VH/VV</td>
<td>6.25 to 50 m</td>
<td>-</td>
</tr>
<tr>
<td>fine, scansar, polarimetric)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terra SAR-X</td>
<td>X</td>
<td>20°-50°</td>
<td>Single, dual, and full polarization</td>
<td>1 – 16 m</td>
<td>&lt; week</td>
</tr>
<tr>
<td>CosmoSky-Med</td>
<td>X</td>
<td>20°-50°</td>
<td>Single, dual, and full polarization</td>
<td>1 - 16 m</td>
<td>&lt; week</td>
</tr>
</tbody>
</table>
### Table 3. Spectral indices used for water detection

<table>
<thead>
<tr>
<th>Name</th>
<th>Calculation</th>
<th>Context</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>NIR</td>
<td>-</td>
<td>Water detection</td>
<td>(Work and Gilmer, 1976)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(White, 1978)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Rundquist et al., 1987)</td>
</tr>
<tr>
<td>NDVI</td>
<td>( NDVI = \frac{NIR - R}{NIR + R} )</td>
<td>The index NDVI was originally used to assess the biomass and vegetation primary production. Nevertheless, it can be of interest to detect water as NDVI shows positive values for vegetation, values close to zero for bare soil and negative values for water.</td>
<td>(Rouse et al., 1973)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Huete et al., 1997)</td>
</tr>
<tr>
<td>EVI</td>
<td>( EVI = 2.5 \frac{NIR - R}{NIR + 6.5B + 1} )</td>
<td>EVI is derived from NDVI, EVI tends to limit the aerosols effects and minimize soil effects.</td>
<td>(Huete et al., 2002)</td>
</tr>
<tr>
<td>NDWI</td>
<td>( NDWI = \frac{G - NIR}{G + NIR} )</td>
<td>NDWI is derived from NDVI, adapted to the delimitation of water bodies with the use of reflectance in the green wavelength.</td>
<td>(McFeeters, 1996)</td>
</tr>
<tr>
<td>NDI2</td>
<td>( NDI2 = \frac{NIR - MIR}{NIR + MIR} )</td>
<td>Initially, Hardisky et al. (1983) showed a correlation between NDI2 and canopy water content. The NDWI (Gao, 1996) and the NDMI (Wilson et al. 2002) were used to detect leaves water content and to assess soil moisture. The LSWI (Xiao et al., 2005) is used to detect soil moisture from MODIS data.</td>
<td>(Hardisky et al., 1983)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Gao, 1996)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Wilson and Sader, 2002)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Xiao et al., 2005)</td>
</tr>
<tr>
<td>MNDWI</td>
<td>( MNDWI = -INH )</td>
<td>The MNDWI is derived from the NDWI defined by Mcfeeters (1996) by the use of middle infrared instead of near-infrared (Xu, 2006). Water bodies are better delineated by a more efficient discrimination between open surface water and dry surfaces. The threshold of discrimination is located around 0. The INH was used by Clandillon et al. (1995) in order to detect humidity in wetland environment. The NDPI was used for detection of small ponds and streams semi-arid areas (Lacaux et al., 2007).</td>
<td>(Xu, 2006)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Clandillon et al., 1995)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(Lacaux et al., 2007)</td>
</tr>
</tbody>
</table>