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# Use of Historical Google Earth Images to Create Likelihood of Aquatic Plants along Segments of Ohio River

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Additional information is available at the end of the chapter

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## Abstract

Aquatic invasive plants are well known for causing severe impacts to local ecosystems, such as degrading water quality, decreasing biodiversity, consuming natural resources, among other impacts. Major water bodies in US had experienced such impacts. To mitigate such impacts, the U.S. Fish and Wildlife Service and the Ohio River Valley Water Sanitation Commission had put significant amounts of effort toward identifying and removing aquatic invasive plants along the Ohio River shorelines. Field work played a significant role in such identification and removal, but at great expense on labor and time. River systems are dynamic, coupled with similarities between spectral reflectance from submerged plants and background water bodies, limited success was reported from literature regarding the use of remote sensing with selected images on detecting aquatic plants. This study utilized Google Earth historical images between 2003 and 2015 along a section of Ohio River known as the Racine Pool and examined and recorded the appearances of aquatic plants. Visible aquatic plants or suspicious submerged objects were digitized and converted to ESRI shapefiles and grids. Spatial analyses and overlays were then performed between grids to derive a map showing frequency of appearance. Such frequency of appearance may serve the purposes of predicting future sighting and/or guides for directing field work in hopes to save labor and time.

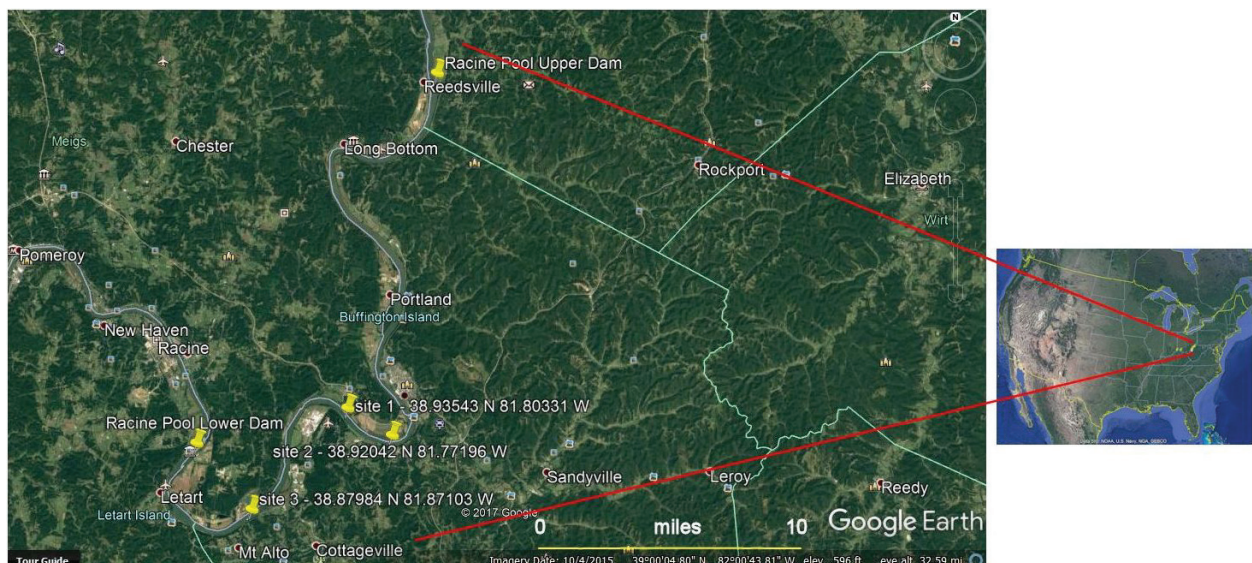
**Keywords:** Google Earth, historical image, Ohio River, aquatic plants, prediction, frequency, remote sensing, GIS

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## 1. Introduction

The proliferation of invasive plants in lakes, ponds, and inland wetlands is of increasing environmental concern; as such plants have the potential to degrade natural ecosystems by compromising water quality, decreasing the usable area of water bodies, and degrading aquatic habitats. Four invasive plant species (purple loosestrife (*Lythrum salicaria* L.), hydrilla (*Hydrilla verticillata*), water-milfoil (*Myriophyllum*), and curly pondweed (*Potamogeton crispus* L.)) have been identified as potential weed threats within the Ohio River Basin [1–4]. Ohio River Valley Water Sanitation Commission has the responsibility of educating people on the facts about the Ohio River, as well as monitor water quality and overall condition of the Ohio River [5]. Field surveys were conducted to survey lakes, ponds, and inland wetlands in this area to identify and monitor the extent of these invasive plants. An effective early detection and warning system utilizing remotely sensed images could greatly benefit the area and significantly reduce labor- and time-costs associated with field surveys.

Though remote sensing had been widely used in various environmental applications [6–8], there were only few studies using remote sensing on detecting submerged aquatic plants. The main difficulty in such a task is the similarity between spectral reflectance from submerged aquatic plants and their background water bodies. It becomes particularly challenging under circumstances where there are high amounts of sediment or suspected particles in the water. Use of remote sensing to identify or detect objects relies heavily on unique spectral reflectance from objects [9, 10]. When such unique spectral reflectance from objects is neither visible nor statistically significant, successful detection or identification of objects will be limited.



**Figure 1.** Study area: the Racine Pool section of Ohio River.

Site	Date	Lat/Long	UTM
Site 1	August 3, 2010	38.93543 N 81.80331 W	430376.315441 X 4309917.960553 Y
Site 2	August 3, 2010	38.92042 N 81.77196 W	433079.384833 X 4308228.797736 Y
Site 3	July 2, 2010	38.87984 N 81.87103 W	424447.956561 X 4303802.923941 Y

**Table 1.** Site locations in Racine Pool section.

### 1.1. Research objective

The research objective of this project is to use time series remote sensing images to derive a likelihood of sighting submerged aquatic plants along a section of Ohio River known as the Racine Pool.

### 1.2. Study area

The study area is the Racine Pool along the Ohio River. It is geographically defined as an upper boundary at 39.118468174 (39° 7' 6") N 81.740928386 (81° 44' 27") W and a lower boundary at 38.914896204 (38° 54' 48") N 81.91346283 (81° 54' 54") W as seen in **Figure 1** from a snapshot of Google Earth. The ground work confirmed the following aquatic invasive plants: site 1 on August 3, 2010 at 38.93543 N 81.80331 W; site 2 on August 3, 2010 at 38.92042 N 81.77196 W; and site 3 on July 2, 2010 at 38.87984 N 81.87103 W. **Table 1** summarizes sites of ground work and associated dates and coordinates, they are also shown in **Figure 1**.

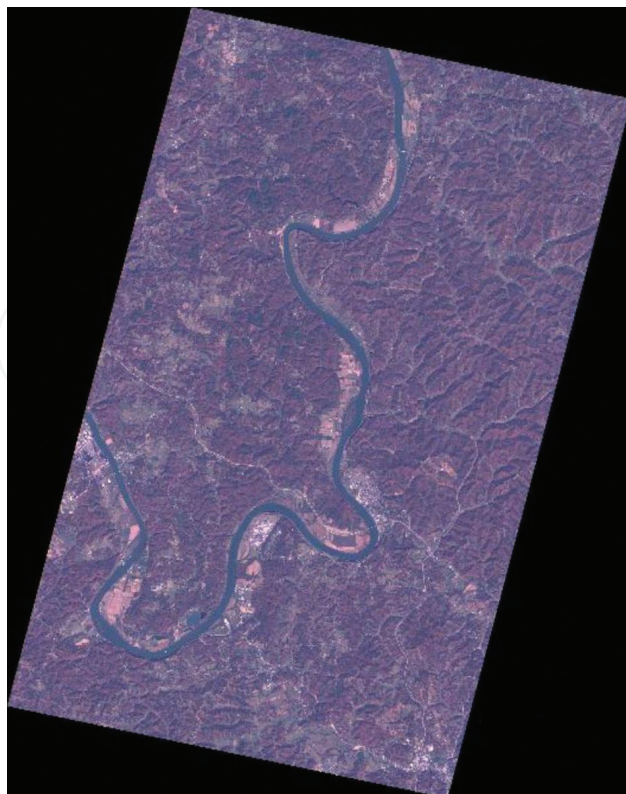
## 2. Previous attempts to identify submerged aquatic invasive plants

### 2.1. Formosat-2 images

Formosat-2 images are unique in regard to their spatial and temporal resolution [11, 12]. Multi-spectral Formosat-2 images contain four bands (blue, green, red and near infrared) at an 8-m pixel size. Panchromatic Formosat-2 images contain one band at a 2-meter pixel size. Therefore, applying proper pan-sharpening processes will result in a multispectral image of four bands with 2-m pixel size. With such superior spatial resolution, these images are capable of monitoring heterogeneous areas, including urban areas. Most impressive is the ability to collect images daily. Due to the satellites' unique design and orbit, it is capable of collecting images of the same area every day, providing unparalleled capacity for monitoring rapid-change events, such as natural diseases.

Formosat-2 is managed by the Taiwan National Space Organization (NSPO). To facilitate world-wide applications, NSPO partnered with the Colorado, US-based Apollo Mapping to sell and distribute Formosat-2 images of the entire world. NSPO maintained the rights to sell and distribute Formosat-2 images of Taiwan. Two scenes of Formosat-2 images of the Racine Pool were acquired on October 28, 2010 (as shown in **Figure 2**) and November 1, 2010 (as





**Figure 2.** Formosat-2 image of Racine Pool section taken on October 28, 2010.

shown in **Figure 3**). **Table 2** summarizes sections of the Ohio River under study and Formosat-2 images acquired.

## 2.2. Image processing and results

According to **Table 2**, there were only 3 or 4 months between the site visit and Formosat-2 image. They were in close proximity in terms of temporal disparity. Upon close visual inspection of the Formosat-2 image, something unexpected drew our attention. As shown in **Figure 4**, site 3 was highlighted on Formosat-2 image with false color display (R,G,B/4,3,2). The Ohio River is a spectrally homogeneous water body, without any major visual spectral anomaly, except shadows from trees along the shoreline. With site visits and confirmed sightings, spectral anomaly was expected around site 3, where the crosshair is.

Several multispectral digital image processing (such as supervised classification, unsupervised classification, principal component analysis, band ratio, and others), regular image processing (such as RGB enhancement, HSV transformation, color clustering, and others), or even single band processing (such as threshold, density slicing classification, edge enhancement, and others) were applied on the Formosat-2 image trying to identify any spectral anomaly. Unfortunately, none of these techniques can identify spectral anomaly with confidence.

With such a disappointing result, the research team started over and reexamined data, ground truth, methodology, and the overall situation. It was soon discovered that river



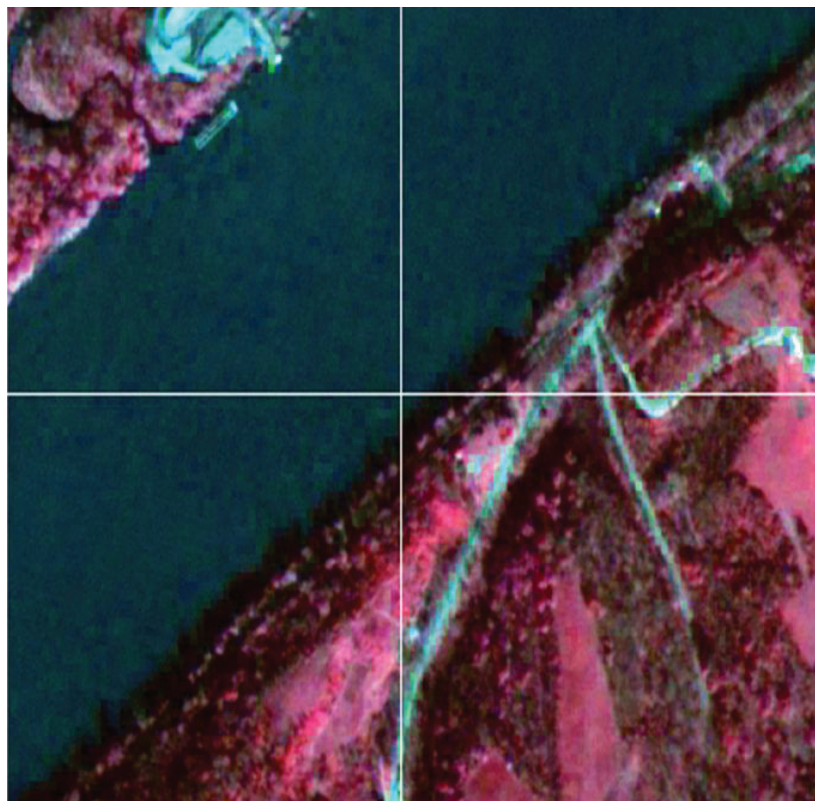
**Figure 3.** Formosat-2 image of Racine Pool section taken on November 1, 2010.

Name	Location	Formosat-2 image date	Ground work date m/d/y
Racine Pool	Upper: 39.11847 (39° 7' 6") N	10/28/2010	#1: 8/3/2010
	81.74093 (81° 44' 27") W	11/1/2010	#2: 8/3/2010
	Lower: 38.91490 (38° 54' 48") N		#3: 7/2/2010
	81.91346 (81° 54' 54") W		

**Table 2.** Sections of Ohio River under study and images acquisition.

dynamics may be the cause for such disappointing results. River ecosystem is dynamic; it changes from time to time due to then-current local environments and weather conditions [13–15]. There are many factors that may affect a river ecosystem, especially how a river looks on satellite images. These factors may include water level, flow velocity, and sediment level, just to name a few.

With such dynamic conditions, working with a single satellite image is like taking a snapshot of a racing car. The satellite image captured the then-current condition, which may only be true to that particular moment but not even the moment before or after. These two Formosat-2 images truthfully recorded the conditions of the Ohio River on 10/28/2010 and 11/1/2010. However, aquatic plants were sighted on 7/2/2010, 4 months prior to the satellite image was taken. During these 4 months, many things may happen and change the overall appearance of a river, which in turn may affect the visibility of aquatic plants.

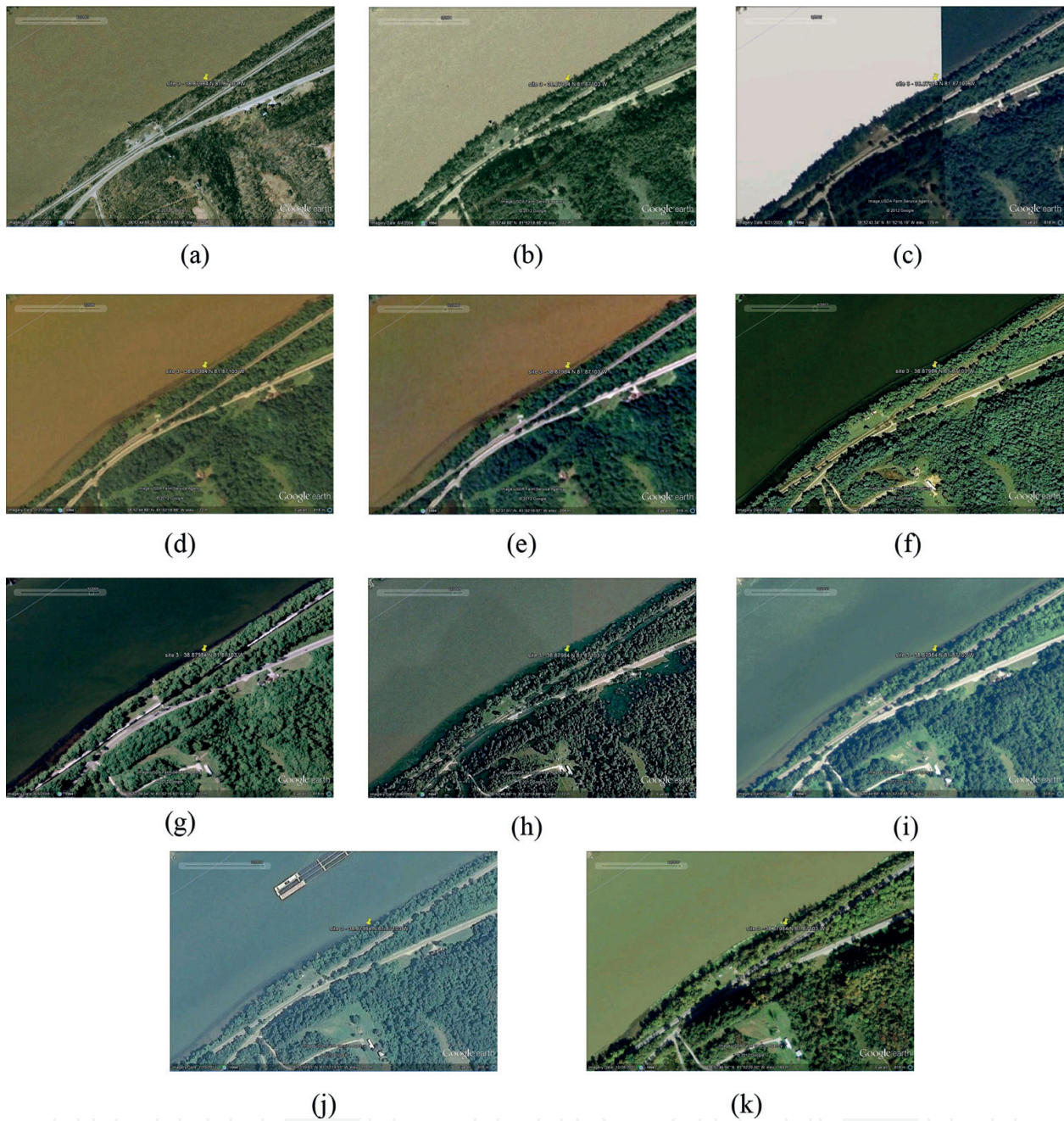


**Figure 4.** Site 3 on Formosat-2 satellite image with false color display (R,G,B/4,3,2).

### 3. Historical Google Earth images

To demonstrate the nature of river dynamics, historical images from Google Earth from 2003 to 2011 were taken and arranged side by side for comparison, as shown in **Figure 5**, with a close-up visual inspection of a particular pair of images (October 2011 in **Figure 5(j)** and November 2011 in **Figure 5(k)**) shown in **Figure 6**. As one may observe from **Figure 6(a)** and **(b)**, there clearly is a linear object appearing along shoreline on **Figure 6(b)**, but it is only faintly visible on **Figure 6(a)**. Just a month apart from each other, the appearance of this aquatic object dramatically changed, proving river ecosystem is dynamic, changing its appearance through time. Thus, the visibility of aquatic object is not consistent, depending on then-current conditions. Knowing this, it is not surprising that this particular aquatic object can be seen in some of the images shown in **Figure 5**, but not others. One may also notice that in **Figure 5(h)**, shadows from trees along the shorelines added confusions and challenges on identifying this aquatic object. These historical Google Earth images and their abilities to visually identify this particular aquatic object are summarized in **Table 3**. Note this: this particular site is site 3 with a confirmed sighting of aquatic plants on 7/2/2010 by field crews during their field work. It is only nature and logic to assume that this spectral anomaly or aquatic object is the reported aquatic plants. It is also safe to conclude that, even with confirmed sighting, the visibility of this particular aquatic plant is not consistent through time as demonstrated in **Figure 5**.





**Figure 5.** Historical Google Earth images of site 3. (a) Image of December 2003, (b) image of September 2004, (c) image of August 2005, (d) image of July 2006, (e) image of October 2006, (f) image of August 2007, (g) image of September 2009, (h) image of October 2009, (i) image of December 2010, (j) image of October 2011, (k) image of November 2011.

## 4. Development of a frequency of sighting map

### 4.1. Warning system and predictive model

Warning system or early warning system had been used in many conservation efforts trying to point out potential threats to a particular ecosystem [16–19]. In many cases, warning system is





**Figure 6.** A close-up visual inspection of (a) October 2011 and (b) November 2011 images.

Google Earth image date	Sub Figure 5	Spectral anomaly
December 2003	(a)	N
September 2004	(b)	N
August 2005	(c)	N
July 2006	(d)	Y
October 2006	(e)	Y
August 2007	(f)	Y
September 2009	(g)	Y
October 2009	(h)	Y
December 2010	(i)	Y
October 2011	(j)	Y
November 2011	(k)	Y

**Table 3.** Dates of historical Google Earth images of site 3.

a result of a predictive model, in which a particular ecosystem is simplified to or modeled by a combination of several factors with associated weights [16, 20, 21]. Success had been reported [18, 19, 22], particularly on solid land where changes are steady or reliable, comparing to aquatic environments.

A critical step in modeling is to identify key factors and their associated weights [23, 24]. These factors and/or weights can be derived from empirical work, literature search, or statistical analysis. In environmental modeling, factors should be something that can be clearly identified and observed in the real world. For example, elevation is to be between 1000 and 1500 m above sea level, slope is to be between 5 and 10°, aspect is to be facing south between southeast and southwest, and so on.

As demonstrated by historical Google Earth images in **Figure 5**, aquatic objects may be visible or not, depending on then-current river conditions. When it is not visible, it does not mean that the aquatic object (aquatic plants in this case) has been removed or is not present. It simply

indicates that the acquired images or photos cannot detect the existence of aquatic objects. They may be disguised. With such uncertainty in appearance, and subsequent ground truthing work, traditional modeling approach may not be suitable or even not workable in aquatic environments. A new approach which is realistic and suitable to aquatic environments is necessary.

Instead of using modeling approach, this study proposed an methodology to survey historical images and create a frequency of sighting map.

#### 4.2. Temporal resolution of remote sensing images

Since the successful launch of Landsat-1 back in 1972, there had been a great wealth of satellite images monitoring our environments. With advances of modern technologies, satellite images are becoming of better quality with more resolution power, such as hyperspectral images with hundreds of spectral bands [25–27] or ultra-fine spatial resolution image with sub-meter pixel size [28–30].

In addition to spatial resolution and spectral resolution, another characteristic of remote sensing systems is temporal resolution or the repetitive coverage of the ground by the system itself. Though remotely sensed images have been widely used to identify vegetation in various conditions [31–33], majority of such projects focused on only selected images to identify objects under study, mainly utilizing spatial resolution or spectral resolution. Temporal resolution, on the other hand, had been overlooked in the mainstream remote sensing research. This study looks to survey historical images of the Racine Pool section of the Ohio River, and it requires a rich image history and a decent temporal resolution.

Google acquired Keyhole Inc., in 2004, and soon launched Google Earth in 2005 [34]. It became a huge hit in the broader geographic information system (GIS) community, as well as the general public. With Google Earth, everyone has free access to satellite images or aerial photos of the entire earth, not only recent images but also historical images. These historical images is an invaluable resource in many environmental projects requiring low cost (or even free) and historical images. Major drawbacks on these historical Google Earth images include inconsistent time interval between images (as short as a month or sometimes as far as years), inconsistent image quality (sun angle, image brightness, color/gray level, pixel size, etc.), lack of image metadata, and so on. Historical Google Earth images was a useful tool and resource to demonstrate the river dynamics earlier in this study. It is selected again as the image source for the new methodology.

#### 4.3. Frequency of sighting from historical Google Earth images

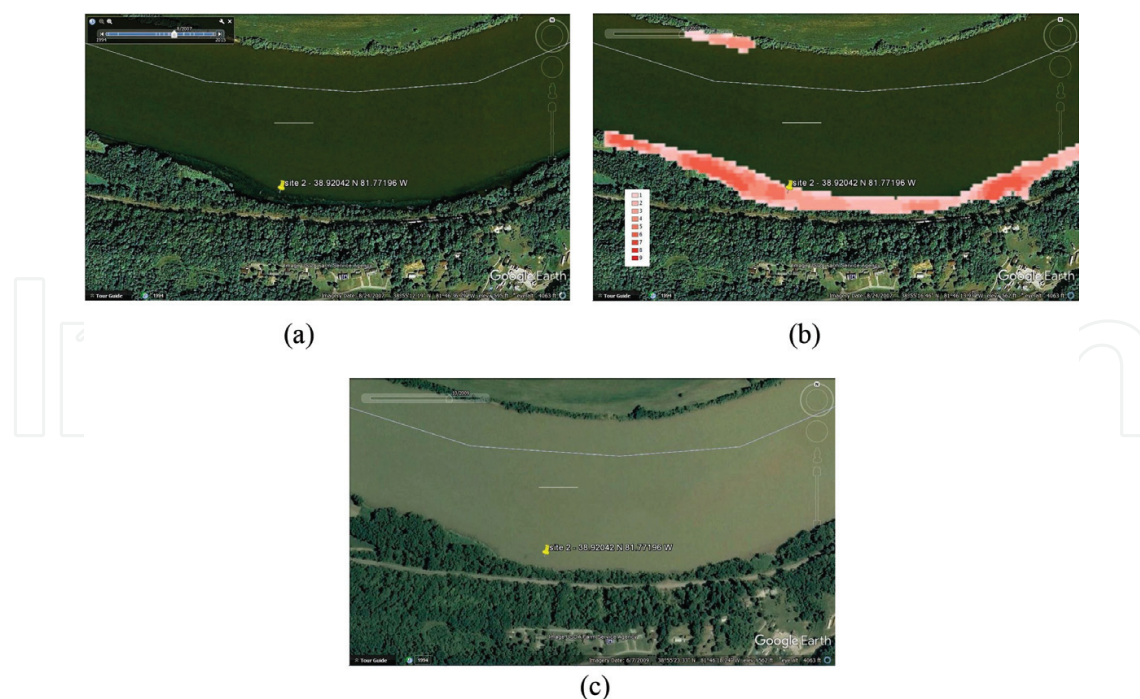
Eleven sets of Google Earth images of the study area between 2003 and 2015 were selected for this project. Though Google provides images before 2003, many earlier images were excluded from this project due to image quality, such as pixel size, color detail, and so on. **Table 4** summarizes year and month of these historical Google Earth images.

Each historical Google Earth image was displayed on computer monitor and visually inspected. If a spectral anomaly is visible during visual inspection, such spectral anomaly was

Google Earth image year	Month
2003	December
2004	September
2005	August
2006	July
2007	August
2009	August
2010	December
2011	October
2012	March
2013	October
2015	October

**Table 4.** Historical Google Earth images selected for this project.

digitized as a KML polygon using available tools from Google Earth. **Figure 7** demonstrates this process. **Figure 7(a)** shows the 08/2007 Google Earth image of site 2, with visible spectral anomalies. Such spectral anomalies were then digitized as a KML polygon using available tools from Google Earth, as shown in **Figure 7(b)**. **Figure 7(c)** shows the 10/2009 Google Earth image of site 2, with no visible spectral anomaly. Therefore, no polygon was digitized for this area.



**Figure 7.** Example of digitizing spectral anomalies from Google Earth images. (a) 08/2007 Google Earth image of site 2 with visible spectral anomalies. (b) Digitizing this anomaly with a KML polygon. (c) 10/2009 Google Earth image of site 2 with no visible spectral anomaly. No KML polygon was digitized on 10/2009 Google Earth image.



After all of the 11 historical Google Earth images were visually inspected and associated KML polygon digitized, a database of polygons showing potential aquatic plants in the study area, by image year, was created. These KML polygons were then converted to ArcGIS shapefile format for some clean-up work, and then converted to ArcGIS grids or raster format for further process. With grids or raster format, all of these spectral anomalies from all of these image years were then analyzed and overlaid through image algebra. The final result is a map or grid showing the frequency of visible spectral anomaly (referred to as frequency of sighting map) in the study area. **Figure 8** shows a portion of the frequency of sighting map, focusing on site 2. The frequency is color-coded, as shown in **Figure 8**. Different colors indicate different frequencies through the surveyed image years. For example, a frequency of 7 indicates that in the surveyed 12 image years, a spectral anomaly (potential aquatic plants) showed up in this particular area 7 times. In such a case, it is a high occurrence rate. Areas of higher frequency indicate more occurrences or sightings in the past. With more occurrences in the past, it is believed that it will lead to higher likelihood of occurrence in the future.

#### 4.4. Discussions

The end results of this study are a frequency of sighting map of aquatic plants in the Racine Pool of the Ohio River. The frequency is obtained from surveying historical Google Earth images. Some of the consecutive Google Earth images are years apart from each other. In a dynamic environment, such long time interval is not ideal. A further study can acquire historical satellite images with reliable temporal resolution to obtain a higher quality of frequency of sighting map.

This frequency of sighting map can serve as a suggestive guide for field work. As budget difficulties rise, performing regular field work may become challenging. A suggestive guide may save time and money on field work. More resources may be directed to areas of higher



**Figure 8.** A portion of the frequency of sighting map showing site 2.

frequency, as they have higher potential of showing aquatic plants and therefore bigger threats to the river ecosystem.

Remote sensing had proven successful on developing a warning system for aquatic plants in the Racine Pool of the Ohio River. Though a warning system is in place, it is still critical to continuously monitor the environment and update the warning system. A future study with secured funding can schedule satellite images with reasonable temporal resolution to continuously monitor aquatic plants.

## 5. Conclusion

River is a dynamic ecosystem, with its appearance changing depending on then-current local environments. A snapshot of such dynamic environment can only truly represent a moment of truth when the snapshot was taken. Previous attempts trying to identify aquatic plants with remote sensing had results in unsatisfying results. Based on lessons learned from previous attempts, this study utilized historical Google Earth images from 2003 to 2015 to identify aquatic plants. Once aquatic plants were identified, they were digitized and overlaid to form a frequency of sighting map. This frequency of sighting map, which indicates the frequency of confirmed aquatic plants in the past 12 years, can serve as a suggestive guide for future field work should budget difficulties restrict or limit resources for field work. In some degrees, it serves the same function as a predictive model.

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