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Using WorldView-2 imagery to track flooding in Thailand in a multi-asset sensorweb

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ABSTRACT

For the flooding seasons of 2011-2012 multiple space assets were used in a "sensorweb" to track major flooding in Thailand. Worldview-2 multispectral data was used in this effort and provided extremely high spatial resolution (2m / pixel) multispectral (8 bands at 0.45-1.05 μ m spectra) data from which mostly automated workflows derived surface water extent and volumetric water information for use by a range of NGO and national authorities. We first describe how Worldview-2 and its data was integrated into the overall flood tracking sensorweb. We next describe the use of Support Vector Machine learning techniques that were used to derive surface water extent classifiers. Then we describe the fusion of surface water extent and digital elevation map (DEM) data to derive volumetric water calculations. Finally we discuss key future work such as speeding up the workflows and automating the data registration process (the only portion of the workflow requiring human input).

Keywords: sensorweb, flood tracking, surface water extent, volumetric water calculation, Worldview-2, multispectral

1. INTRODUCTION

Rapid growth in available commercial remote sensing can enable greatly enhanced environmental monitoring. Recently launched satellites make available extremely high spatial resolution multispectral imagery. However in order to provide high spatial resolution data, these satellites are point-and-shoot, that is to say that they are typically targeted observations that must be requested prior to overflight.

Sensorweb operations is a concept of operations in which data from multiple satellites is assimilated to better track some event or environmental phenomenon. In the sensorweb concept, data is assimilated from satellites and other sources, and used to model and track the phenomena of interest and drive future targeting. The key is that the modeling and tracking provide timely and detailed information. The desire to provide detailed information means that the highest spatial resolution information is typically desired. The desire to provide timely information means that ideally the data acquisition, processing, and modeling is done automatically. If future targeting can be automated (e.g., [Chien et a. 2011]), subsequent data will enable continuous precise modeling.

Worldview-2 is a satellite launched and operated by DigitalGlobe that has extremely high-resolution (2m / pixel) spatial resolution combined with significant multispectral (8 bands at 0.45 – 1.05 μm) capability. In this paper we explore the use of Worldview-2, in a sensorweb used to track flooding in Thailand over the period 2010-2012. Flooding has a tremendous impact on humanity and is worldwide in scale. From p. 348, [NRC 2007] "Floods are among the most destructive of natural disasters. From a monetary standpoint, flood damages in the United States averaged around $5 billion per year in the 1990s in 1995 dollars (Table 3.1 in Pielke et al., 2002). Outside the United States, the impact is even more striking; flood losses globally increased 10-fold (inflation-corrected) over the second half of the 20th century to a total of around $300 billion in the decade of the 1990s [Kabat and van Schaik, 2003]."

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Thailand (as well as greater southeast Asia) is particularly prone to flooding as observed during the sensorweb operational usage in the 2010 and 2011 flooding seasons in Thailand. The Thailand flooding of October-November 2010 [MCOT 2010, Bangkok Post 13 Nov 2010, Wikipedia 2010] was responsible for over 200 deaths, over $1.67 Billion USD damage, and affected over 7 million people [CNN 2010]. The Thailand flooding in 2011 was even more severe (See Figure 1) accounting for over 600 deaths and $45.7 Billion USD damage [World Bank 2011]. As this article goes to review in February 2012 the floods have not yet fully receded and the full extent of the damage is still not yet known.

Flooding is also a key part of the global hydrologic cycle. "The scientific challenge posed by the need to observe the global water cycle is to integrate in situ and space-borne observations to quantify the key water-cycle state variables and fluxes." [NRC, 2007].

This paper describes how Worldview-2 multispectral data can be used to automatically map surface water extent areas with very high (2m) spatial resolution. We then describe how this surface water extent map can be combined with digital elevation map data to estimate water volume for flooded areas. This capability, within the deployed flood monitoring sensorweb represents a unique capability in flood monitoring.

2. AUTOMATED FLOOD PROCESSING OF WORLDVIEW-2 DATA

2.1 Worldview-2 data, Radiometric and atmospheric correction

The Worldview-2 data we used for this study was acquired in the southeast Asia region (principally focused on flooding of the Chao Praya river near Bangkok, Thailand) in the November 2011 timeframe. The scenes are typically 6 km by 16 km at 2m/pixel and 8 spectral bands. These images are first converted to top-of-atmosphere reflectance [DigitalGlobe] for subsequent processing.

2.2 Surface water extent calculation

We have used support vector machine (SVM) [Schölkopf & Smola, 2002] techniques to learn classifiers to automatically detect flooded areas in WorldView-2 (WV-2) data. We process images of flooded regions converted to reflectance as described above. In order to train the SVM classifier, we first hand labeled several images for border, water, and land (including urban) areas.

We experimented with different SVM kernels and parameters, and have trained SVM classifiers using either (a) a feature set of the 8 multispectral WV-2 bands and (b) a feature set of each of the 28 ratios between bands. Labeling, training, validation (quantitative and qualitative) and kernel-parameter selection, were done through the Pixellearn tool [MLIA]. In our experience, linear kernels often produced excellent results for the scene they were trained on, but performed poorly on other scenes. Through manual and qualitative selection, a polynomial kernel of degree 5 and a cost factor (C) of 1.0 was chosen for satisfactory performance across multiple scenes. Running directly within PixelLearn, this classifier could classify a scene within about five minutes. We experimented with training a more sophisticated classifier to distinguish additional classes (urban areas and clouds), but this did not generalize well to multiple scenes. For this extended classifier, the runtime within PixelLearn increased from several minutes to about two hours. We also tested this classifier with a classification program written in Python, where runtime increased to up to 1.5 days for a single WV-2 scene.

We trained the 5th-degree polynomial classifier using the three classes (border, water, land) on a scene of Bangkok taken on November 8, 2011 (Catalog ID: 2020010091157400). We ran this classifier for two other scenes taken on November 3 and November 8 (Catalog IDs: 2020010090403A00 and 2020010091155C00, respectively). The confusion matrices for the 3-class (border, water, land) 5th-degree polynomial SVM run on the hold-out scenes of Bangkok are shown in Table 1 and Table 2. We also ran this protocol using the band ratios as the features with the results shown in Tables 3 and 4. The November 3 scene and its SVM classification are shown in Figure 1 (upper-left and lower-right, respectively).

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We also trained using a linear and radial basis function (RBF) / Gaussian kernel SVM. The linear SVM works well for the scene it is trained on but performs poorly for other scenes. Surprisingly the RBF SVM has inconsistent results, sometimes performing similar to the polynomial and sometimes worse.

In addition to the SVM, we ran a thresholding algorithm applied to the ratio of WorldView-2's NIR1 / green bands (selected because of their similarity to the bands used in [Ip et al. 2006, Chien et al. 2011]. Regions with a ratio above the threshold were marked as land, and those below as water. A threshold of 0.8 yielded a water classification map comparable to that for the SVM, shown Figure 1 (lower left).

Table 1: Confusion Matrix for SVM-classified scene taken November 3. Features = bands. Kernel=degree 5 poly

Class	**Unlabeled**	**Border**	**Water**	**Land**
Unlabeled	0	13156222	20395227	45959337
Border	0	223	0	0
Water	0	0	6847	338
Land	0	0	0	1044

Table 2: Confusion Matrix for SVM-classified scene taken November 8. Features = bands. Kernel=degree 5 poly

Class	**Unlabeled**	**Border**	**Water**	**Land**
Unlabeled	0	25639043	12807455	22806048
Border	0	349	0	0
Water	0	0	2206	287
Land	0	0	3	3110

Table 3: Confusion Matrix for SVM-classified scene taken November 3. Features = band ratios. Kernel=degree 5 poly

Class	**Unlabeled**	**Border**	**Water**	**Land**
Unlabeled	0	13156222	19540101	46728134
Border	0	223	0	0
Water	0	0	6845	340
Land	0	0	0	1044

Table 4: Confusion Matrix for SVM-classified scene taken November 8. Features = band ratios. Kernel=degree 5 poly

Class	**Unlabeled**	**Border**	**Water**	**Land**
Unlabeled	0	25639043	12601354	22999969
Border	0	349	0	0
Water	0	0	2270	221
Land	0	0	4	3109

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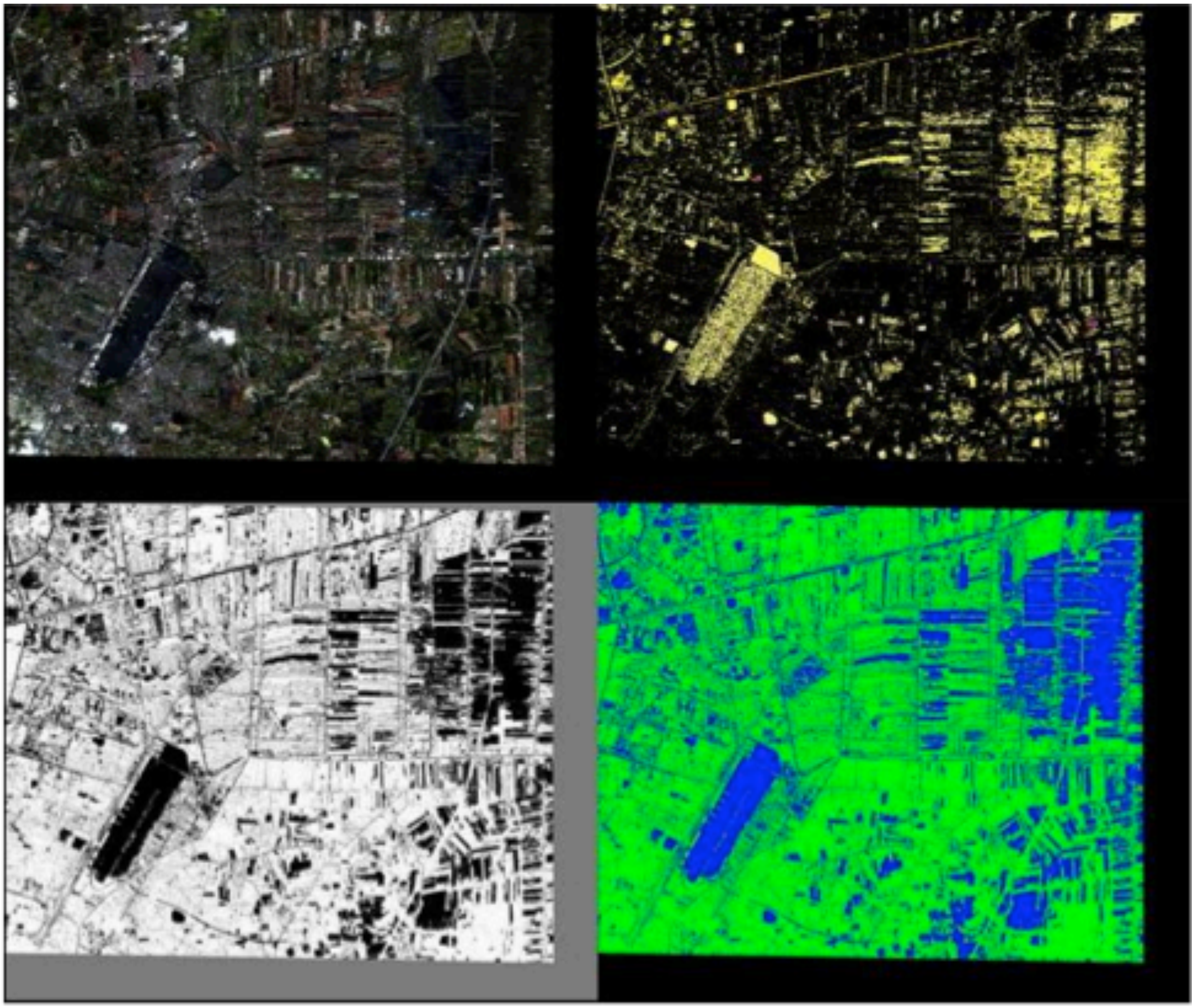

Figure 1: RGB image of WV-2 scene (Catalog ID: 2020010090403A00) taken November 3, 2011 (upper left);
water depth map: pale yellow = 0 meters, blue = 9m (upper right);
band ratio water extent map: black=water (lower left),
SVM surface water extent map: green=land, blue=water (lower right)

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2.3 Volumetric water calculation

We have created a workflow that uses surface water extent classification results from a sensor (including MODIS, ALI, WorldView-2, or Radarsat2 raster GeoTIFFs), calculates pixel heights using a digital elevation model (DEM), and estimates the depth of flood-water pixels by estimating their elevation from their boundary. Because the program reads classified images as input, it generalizes well to a large suite of instruments: any classification data that can be saved in a GeoTIFF can be used in this approach. We tested this system using scenes of flooding in Bangkok during November 2011, and obtained a DEM of the Bangkok & Ayutthaya region of Thailand, with 5m horizontal and 1m vertical resolution, from Thailand's Hydro and Agro Informatics Institute (HAII).

The procedure used to estimate water depths of flooded pixels is roughly as follows:

1. Identify all land, water, and no-data pixels from classification results, and all pixels that lie on the boundary between land & water bodies. Boundary pixels can include both land pixels next to water, and water pixels adjacent to land; our software includes a switch to select which pixels constitute the boundary. No-data pixels represent anything that is not land or water, including image borders and clouds.
2. Identify all unique, 8-connected water bodies in the image, and create a grid f with the same size as the input image, containing the feature label for each pixel (i,j). A feature number of $f[i,j] = 0$ indicates that the pixel is not a water pixel.
3. For all water and boundary pixels (i,j), estimate the height of the pixel $h[i,j]$, using the following procedure. Given a geolocated DEM and the input classification image's horizontal resolution R (in meters), we estimate height by finding the nearest pixel in the DEM corresponding to the lat-lon location of (i,j) in the classification map, constructing a box around this pixel with side length R, and setting $h[i,j]$ to the average of all the DEM pixel values found inside this region.
4. For each water body f, estimate water elevation:
    1. Store a list of elevations of boundary pixels for the feature, *boundary[f]*
    2. Initialize feature elevation $E[f] = 0$
    3. if (length(*boundary[f]*) > 0) then $E[f] = mean(boundary[f])$
5. For all water pixels (i,j), calculate depth:
    1. if($f[i,j] > 0$) then $d[i,j] = \max(0, E[\, f[i,j]\,] - h[i,j])$

The program, written in Python, outputs a GeoTIFF giving per-pixel water depth, with the same resolution and geolocation as the input classification map. Computing the water depth map for a classified WorldView-2 scene takes 1-2 hours. The water depth output for the scene shown is in the upper-right corner of Figure 1 The total water volume calculated within this scene is approximately 27,872,000 cubic meters, and the average depth of flooded pixels is 0.64 meters. We computed the depth map for this scene and forwarded it to HAII during the Thailand flood season. We have computed the water depth map for other scenes, but we have not distributed more of these products.

Several factors can impact the accuracy of this method. The classification of WV2 images itself is not perfect, and not all land and water pixels can be reliably identified. The DEM data is also noisy; regions that would be expected to be flat in practice can be a mixture of pixels that differ by 1 meter in elevation. In the DEM itself, a 1 meter jump in elevation represents a very large change compared to the roughly 2 meter average elevation for the city of Bangkok. An elevation model with higher resolution would reduce noise and error in the water depth results.

The water volume program can also read cloud pixels from input surface water extent maps, although as described previously, we did not use these for WorldView-2. It is difficult to decide what to do with cloud pixels if they are used, since it is unknown if they are flooded or not. It would be desirable to determine the status of these pixels based on the status of their neighbors. Currently, cloud pixels are treated as if they contain no data.

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Finally, this method assumes that water level can be inferred by equating it with the elevation of surroundings, but this may not necessarily be true in urban environments.

3. USE OF WORLDVIEW-2 DATA IN THAILAND CAMPAIGN

3.1 Campaign

During the 2011-2012 Thailand flooding scene numerous Worldview-2 scenes of the flooding in the Bangkok region were acquired. The table below indicates the scenes we were able to process – all of which were from the November 2011 timeframe. These sixteen (16) images allow for precise tracking of the flood damages and extent in the lower Chao Praya region near Bangkok, Thailand. During this time period and afterwards, we processed this flood related data (as well as other acquired data) and delivered surface water extent and water volume estimation products to HAII and Thaiflood.com for subsequent distribution to interested institutions.

Table 5: Worldview-2 Scenes processed from Bangkok, Thailand Flooding Campaign, November, 2011

Scene filename	Catalog ID	Acq. Date
03NOV11WV020300011NOV03042243-M1BS-052611834010_02_P005	2020010090406500	11.3.2011
03NOV11WV020300011NOV03042256-M1BS-052611834010_01_P001	2020010090403A00	11.3.2011
03NOV11WV020300011NOV03042257-M1BS-052611834010_01_P002	2020010090403B00	11.3.2011
03NOV11WV020300011NOV03042258-M1BS-052611834010_01_P003	2020010090404F00	11.3.2011
03NOV11WV020300011NOV03042259-M1BS-052611834010_01_P004	2020010090405400	11.3.2011
03NOV11WV020300011NOV03042301-M1BS-052611834010_01_P005	2020010090404500	11.3.2011
03NOV11WV020300011NOV03042313-M1BS-052611834010_03_P001	2020010090408A00	11.3.2011
03NOV11WV020300011NOV03042314-M1BS-052611834010_03_P002	2020010090408F00	11.3.2011
03NOV11WV020300011NOV03042316-M1BS-052611834010_03_P003	2020010090409300	11.3.2011
03NOV11WV020300011NOV03042318-M1BS-052611834010_03_P005	2020010090407800	11.3.2011
08NOV11WV020300008NOV11043913-M1BS-052616389010_01_P003	2020010091153000	11.8.2011
08NOV11WV020400011NOV08043911-M1BS-052616389010_01_P001	2020010091157400	11.8.2011
08NOV11WV020400011NOV08043912-M1BS-052616389010_01_P002	2020010091154100	11.8.2011
08NOV11WV020400011NOV08044001-M1BS-052616389020_01_P001	2020010091155C00	11.8.2011
08NOV11WV020400011NOV08044002-M1BS-052616389020_01_P002	2020010091157600	11.8.2011
11NOV08044003-M1BS-052616389020_01_P003	2020010091155D00	11.8.2011

3.2 Related Work

A number of flood related products such as surface water extent have been derived from remote sensed imagery. MODIS [Brakenridge and Anderson 2005, DFO, Carroll et al. 2009, Doubleday et al. 2011] enables great coverage but moderate resolution (250/pixel). The Earth Observing One Advanced Land Imager (EO-1/ALI) offers better spatial resolution (30m/pixel) with reduced temporal and spatial coverage [Chien et al. 2011, Doubleday et al. 2011]. Earth Observing One Hyperion offers excellent spatial resolution with poor spatial coverage [Ip et al. 2006]. A range of radars offer excellent all weather capabilities but with modest coverage and resolution [Doubleday et al. 2011a,b, Briscoa et al. 2008, Kussul et al. 2011, Dubois et al. 1995]. The Dartmouth flood observatory has used AMSR-E [DFO] and Quikscat as well to track flooding but with lower spatial resolution.

3.3 Lessons learned and future work

From the November 2011 tracking of Bangkok flooding, we also have multispectral imagery from Ikonos (5 scenes) and GeoEye (3 scenes). We are exploring processing this data using both band ratio and SVM surface water extent classification methods to allow better temporal tracking of the flooding events. Additionally, we have access to some in-situ telemetered data and hydrological models via a collaboration with the Hydro Agro Institute of Thailand. This in-situ data and modeling could further enhance flood tracking. We also wish to explore if processing pan-sharpened data would improve accuracy. Finally, TRMM provides cumulative rainfall data that could also be integrated into the flood modeling to improve accuracy.

4. CONCLUSIONS

We have described the use of Worldview-2 in an earth observing sensorweb to track flooding in Thailand during the November 2011 flooding. In this sensorweb Worldview-2 provided multispectral data of very high spatial resolution (2m/pixel). We used SVM machine learning techniques to train classifiers to process this imagery into surface water extent maps. These surface water extent maps were then combined with digital elevation map (DEM) information to estimate water volumes. These flood products were automatically delivered to relevant Thailand institutions to support tracking and decision-making activities. These sensorweb techniques and ongoing enhancements represent a powerful tool in tracking and mitigating natural hazards.

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