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Mapping Water Bodies in Tropical Regions under Mixed Inundation. Application to Rosieres Reservoir

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ملخص البحث:

يحتوى حوض نهر النيل وخصوصا أعالى النيل على مسطحات هائلة من المستنقعات والمسحات المائية الأخرى التى تحتاج الى متابعة دورية ومنتظمة نظرا لأهميتها فى فهم الميزان المائي لحوض النيل. يعد اعداد خرائط دورية للمسطحات المائية فى المناطق الاستوائية أمرا شديد الصعوبة وذلك لقلة المعلومات والقياسات المتاحة فى هذه المناطق وخصوصا اثناء الفيضانات. يهدف هذا البحث الى وضع تقنية اوتوماتيكية واسلوب عمل جديدين ومتكاملين لمواجهة هذه التحديات واعداد خرائط للمسطحات المائية ذات دقة افقية عالية ومعدل تكرار زمنى مناسب ومنتظم. تم استخدام صور القمر الصناعى (MODIS) وتحميل البيانات من كل من منصات (TERRA) و (AQUA) لمنطقة الدراسة للفترة من عام ٢٠٠٠ حتى عام ٢٠١٤. تم استخدام طريقة Open Water Likelihood (OWL) بعد اثبات حساسيتها فى الكشف على المياه خصوصا عند تداخل المياه مع التربة والغطاء النباتى. تم التغلب على الغطاء السحابى بأكبر قدر ممكن من خلال الجمع بين بيانات AQUA و TERRA واستخدام بيانات ال ٨ أيام المركبة لكل منصة لتقليل الفجوات بقدر الامكان هذا بالإضافة إلى تطبيق منهج إحصائي كفئ لملء الفجوات المتبقية. تتم معايرة الخرائط المحسوبة من OWL بخرائط مياه ناتجة عن تحليل صور أقمار صناعية أخرى أعلى بكثير فى الدقة الأفقية مثل Landsat ETM+ وLandsat OLI. تم بعد هذا تطبيق النسبة OWL المثلى لاعداد سلسلة زمنية من خرائط المياه لخزان سد الروصيرص من عام ٢٠٠٠ حتى عام ٢٠١٤. تتوافق الخرائط المحسوبة الى حد كبير مع القياسات الأرضية المتاحة للخزان. أثبتت التقنية الجديدة التي وضعت كفاءة عالية فى اعداد خرائط للمسطحات المائية الداخلية تحت ظروف الغمر المختلطة.

Abstract:

Continuous monitoring of inland water bodies like lakes, reservoirs, and wetlands is an essential part for successful water resources management. The Upper Nile basin contains vast areas of wetlands and water bodies that need continuous monitoring as huge amount of water is lost yearly through them in the form of evaporation and seepage. Understanding the water budget of these inland water bodies is not possible without knowing the inundation extent on a consistent spatial and temporal basis. Mapping wetlands in tropical regions is a highly challenging process due to lack of field measurements and extreme cloud cover. The aim of this study is to introduce a more accurate, robust, and automated technique to define the extent and variation of inland water bodies in tropical regions all the year round. Due to lack of measurements and ground data, the introduced technique depends mainly on remote sensing and Earth observation data collected from space. MODIS data is selected for its high temporal (1-2 times daily) and spectral resolution. Data from both the Terra and Aqua platforms is downloaded for the study area for the period from 2000 till 2014. Several water detection techniques are assessed and the Open Water Likelihood Index (OWL) is adopted for its proved sensitivity in detecting water over mixed inundated pixels of water, bare soil, and vegetation, calculating fraction of water for each pixel. As with all optical sensors, cloud contamination represents a great challenge to using

the data directly. This is controlled as much as possible by combining data from 8-day composites from both platforms in addition to applying a statistical approach for filling in the remaining gaps. Due to lack of ground truth data, daily OWL maps are compared to water maps generated from the much higher spatial resolution Landsat ETM+ and OLI sensors for certain times of the year and showed substantial to strong agreement. An optimum OWL threshold has been determined and applied to generate a time series of water maps over the Roseires Dam Reservoir from 2000 till 2014. The generated time series agrees well with ground measurements. The developed methodology proved to be both efficient and consistent is mapping inland water bodies under mixed inundation conditions
Keywords: Remote Sensing, Wetlands, MODIS, OWL, Roseires Dam, Mixed Inundation, Gap Filling.

1. Introduction:

Continuous monitoring of inland water bodies like lakes, reservoirs, and wetlands is an essential part for a successful water resources management. Providing consistent spatial and temporal maps for inland water bodies is essential to help understanding and identifying changes in their ecosystems. Special concern worldwide is directed to water bodies in tropical regions as they present about half of the world's wetland areas (H.U. Neue et al, 1997) and they play a vital role in the global carbon and water cycle (The Kyoto and Carbon initiative, Jaxa, Japan, 2009).

The Upper Nile basin contains vast areas of wetlands and water bodies that are either permanent or seasonal. Since huge amount of water is lost yearly from these water bodies in the form of evaporation and seepage, understanding the water budget of these inland water bodies is not possible without knowing the inundation extent on a consistent temporal basis.

Mapping water bodies in tropical regions is a highly challenging process due to: limited accessibility during high floods, limited or no ground data available including surveys, flow and water level measurements; and typically extreme cloud cover especially during the rising stage of flood where maximum inundation of water bodies is expected. In addition to the above, water runs between vegetation and bare soil making the delineation process more challenging.

The science of detecting water from space has improved significantly during the last years due to the invention of new advanced passive and active satellite sensors that orbit the earth all the time. It has been proven that remote sensing data and techniques can be used to detect water and monitor floods efficiently (Ralf W. Tiner et al., 2015). In order to capture variation in water bodies throughout the year given the lack of data and inaccessibility during flood events, it is required to routinely acquire freely available remote sensing data which have regional coverage at an acceptable spatial resolution.

Landsat imagery can provide the appropriate spatial detail for hydrological modeling, but its temporal frequency of 16 days is not suited to capturing the temporal dynamics of many flood events. In addition, acquiring images every 16 days reduces the chance of collecting enough cloud free images of the study area. Other high resolution optical sensors like Quickbird, IKONOS, SPOT, etc…. also do not provide the required temporal resolution in addition to the high cost of acquiring data for large study areas. On the other hand, NASA's Moderate Resolution Imaging Spectro-radiometer (MODIS) sensors have proven high efficiency in mapping surface water at moderate spatial resolution (250 – 1000m). The medium resolution of the MODIS sensors make it not suitable to map smaller and narrow water features, however, MODIS still provides consistent temporal monitoring by acquiring images 2 times daily for the same location from two platforms; the TERRA platform (10:00am) and AQUA platform (1:00pm) (Ticehurst et al., 2013). Landsat data has been used many times in the literature as "ground truth" data to validate the inundated flood plain from MODIS due to its relatively high spatial resolution (Guerschman et al, 2011).

All historical MODIS data are readily available for the whole world from year 2000 till present and can be downloaded from the NASA LPDAAC website. MODIS bands 1 (Red) and 2 (NIR) are at 250m pixel size and have been used to capture large global flood events through the Dartmouth Flood Observatory (Brakenridge and Anderson 2006), as well as environmental monitoring of seasonal flood patterns on floodplains (Ward et al., 2013). This is further enhanced later through NASA Near Real Time (NRT) MODIS Global Flood Map where daily MODIS flood maps are produced at a global scale of 250m spatial resolution (Beta Science product is released in October 2014).

Techniques for using MODIS data for detecting water bodies and estimating flood plain inundation are continuously evolving. Given the strong sensitivity of the SWIR (Short Wave Infrared) wavelength to water, MODIS SWIR bands 6 and 7 (500m pixels) have been used for inundation mapping through the use of indices such as the Normalized Difference Water Index (NDWI) (McFeeters, S.K., 1996), and the modified Normalized Difference Water Index (mNDWI) (Xu, 2006). The above mentioned methods have been proved to be most effective for open water bodies where most of the pixels are pure water with no mixed inundation.

Due to the large size of the MODIS pixel, it's more likely to have pixels with mixed water-vegetation or water-bare soil reflectance. This is typically the case in detecting water bodies and wetlands in the Upper Nile Basin. New methods have been introduced to calculate the fraction of water in a MODIS pixel. Water fraction mapping of MODIS pixels has been applied by Weiss and Crabtree (2011) who used the Normalized Difference Vegetation Index (NDVI), NDWI and tasseled cap to derive water fraction at a 1 km pixel with reasonable accuracy but it was computationally intensive (Ticehurst, et al, 2013).

The method adopted in this study to detect water bodies under mixed inundation is the Open Water Likelihood (OWL) Algorithm that was developed by Guerschman et al, 2011. The method has been verified through several studies that it is sensitive to capture the dynamics of water movement when compared to stream flow data for large regional scales (Ticehurst et al, 2014). Ticehurst also stated that "The MODIS OWL algorithm has proved to be the best to date mapping tool for flood plains". This will be discussed later in the following sections.

The target of this study is to develop a new complete workflow for delineating water bodies in tropical regions under mixed inundation. The workflow relies on applying the MODIS OWL algorithm to MODIS satellite images after being calibrated against ground truth data such as ground measurements or higher resolution water maps. A robust Gap filling technique is then applied to overcome the problem of extreme cloud cover that is characteristic for tropical regions and limits the usefulness of optically collected remote sensing data. The workflow, once calibrated, provides consistent spatial and temporal maps for inland water bodies through a fully automated process that require minimum human input. The methodology is then applied to create a map time series of water body extent for the Roseires Reservoir that is located on the Blue Nile, Upper Nile Basin.

2. Materials and Methods:

2.1. MODIS OWL Algorithm:

In the MODIS OWL algorithm, Guerschman et al. (2011) used a detailed empirical approach with the MODIS bands, utilizing the strong relationship between NDVI, NDWI, the SWIR bands, and other factors calculated from Digital Elevation Models (DEM), producing fractional water coverage at 500m pixel size. One of the advantages of the OWL algorithm is that it is fast and easy to apply on multi-temporal datasets, compared to more complex algorithms. The MODIS OWL method developed by Guerschmann et al. (2011) calculates the fraction of water within a MODIS pixel by:

$$f_w = \frac{1}{1+\exp(z)} \qquad \text{Eq. (1)}$$

where, z is defined as:

$$z = \beta_0 + \sum_{i=0}^{5} \beta_i . x_i \qquad \text{Eq. (2)}$$

f_w is the estimated fraction of standing water, x_i are independent variables, and β_i are parameters fitted empirically. The values of β for different i are defined as follows:

$\beta_0 = -3.41375620$
$\beta_1 = -0.000959735$ x_1 = SWIR band 6 (reflectance*10000)
$\beta_2 = 0.00417955330$ x_2 = SWIR band 7 (reflectance*10000)
$\beta_3 = 14.1927990$ x_3 = NDVI
$\beta_4 = -0.430407140$ x_4 = NDWI (Gao, 1996)
$\beta_5 = -0.0961932990$ x_5 = MrVBF (Gallant and Dowling, 2003)

MrVBF is the Multi-resolution Valley Bottom Flatness index as described by Gallant and Dowling, 2003.

The NDVI for MODIS data shall be calculated as

$$NDVI = \frac{\rho_{NIR}-\rho_{RED}}{\rho_{NIR}+\rho_{RED}} = \frac{Band\ 2-Band\ 1}{Band\ 2+Band\ 1} \qquad \text{Eq. (3)}$$

The NDWI for MODIS data shall be calculated as

$$NDWI = \frac{\rho_{NIR}-\rho_{SWIR}}{\rho_{NIR}+\rho_{SWIR}} = \frac{Band\ 2-Band\ 6}{Band\ 2+Band\ 6} \qquad \text{Eq. (4)}$$

The Multi-resolution index of Valley Bottom Flatness (MrVBF) of Gallant and Dowling (2003) identifies areas that are low and flat relative to the surrounding topography. Large MrVBF values indicate broad and flat valley bottoms where the maximum value represents the broadest and flattest area in the landscape. Typically, values below 0.5 identity areas either too steep or too high to be valley bottoms (Gallant and Dowling 2003). The MrVBF is calculated from Digital Elevation Model (DEM) in an iterative process that is described in detail in Gallant and Dowling, 2003.
Ticehurst et al. (2014) performed a thorough assessment of the MODIS OWL algorithm and compared the results with other MODIS flood products including the NASA NRT Global Flood Maps. The MODIS OWL algorithm has proved to be the best to date mapping tool for flood plains provided that the following precautions are followed:

- Select MODIS OWL values of at least 6% water as it eliminates most commission errors and reduces noise in the data
- Use daily MODIS OWL data of low view angle (range distance less than 1000 km) where possible
- In some cases it may be necessary to exclude pixels having a low relative azimuth angle (i.e., the angle between the MODIS' and sun's azimuth angles) as this introduces commission errors in some spectrally dark pixels. However, a flood likelihood mask will also reduce the number of spectrally dark pixels which may be confused with water.

Despite the above limitations, daily MODIS OWL water maps have already been used for wetland inundation mapping (Chen et al., 2013), estimating overbank flood recharge (Doble et al., 2014), as well as assisting in the calibration of hydrodynamic models at different stages of a flood event (Karim et al., 2013), all with varying degrees of success. When compared to upstream and downstream flow measurements for the Fitzroy River and Macquarie Marshes (both in Australia) during a large flood event, the daily MODIS OWL water extent shows temporal changes as expected (Ticehurst et al., 2013).

Ticehurst et al. (2013) and Chen et al. (2013) have shown that the MODIS OWL can effectively map medium to large water features when compared to an equivalent Landsat water map, but lacks the detail around the edge of a flood or along narrow water features where it tends to underestimate the water extent. Ticehurst et al. (2014) proved that the MODIS OWL is better at identifying fine water features and open water bodies with MODIS data than the commonly used modified NDWI by Xu, 2006.

2.2. Study Area:

The Roseires Dam is located on the Blue Nile at 11°47'54.45"N and 34°23'15.51"E. The reservoir extends for about 52km upstream the dam and the estimated maximum storage was about 3 km^3 before being heightened in 2012. The water level and storage in the reservoir vary significantly during the year reaching its maximum storage in October and November and is almost dry in August. The surface area corresponding to the 3 km^3 storage is about 290km^2. All the available data for the reservoir are obtained from the Nile Decision Support System (Nile DSS) for the period before 2012 (before the dam being heightened). In this study, the developed methodology shall be applied to obtain a time series for reservoir area variation for the Roseries reservoir from Feb-2000 till Dec-2014. Figure 1 shows the extent of the study area covering the Roseires reservoir.

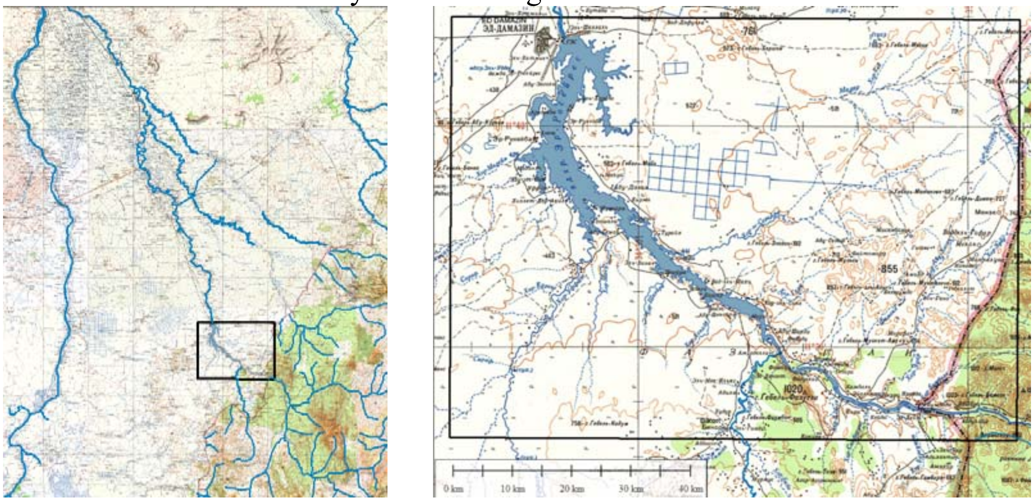


Figure 1: Roseires Reservoir Study area

2.3. Preprocessing MODIS Data

In this study, the algorithm shall be applied to the 8-day composites products from both the TERRA (MOD) and AQUA (MYD) platforms. In the 8-day composite product, each pixel contains the best Level 2G observation during an 8-day period with respect to cloud cover, sensor to pixel distance, and aerosol loading. It has been proved in the literature that the 8-day composite products can still describe the dynamics of fast moving flood events when compared to the daily products but with the benefit of decreasing cloud cover to a great extent (Ticehurst, 2013). Bands 1 and 2 are obtained at 250m resolution from MOD09Q1 and MYD09Q1 products for the TERRA and Aqua platforms respectively. Similarly, the remaining bands needed for calculating the OWL algorithm are obtained at 500m resolution from the MOD09A1 and MYD09A1 products. All tiles covering the study area are downloaded as per Table 1.

Table 1: Downloaded MODIS tiles for the study area (Collection 5)

Product	Start Date	End Date	Number of Downloaded Tiles
MOD09A1 (Terra)	26-2-2000	31-12-2014	682
MYD09Q1 (Terra)	26-2-2000	31-12-2014	682
MYD09A1 (Aqua)	1-1-2003	31-12-2014	553
MYD09Q1 (Aqua)	1-1-2003	31-12-2014	553

The downloaded tiles were projected to UTM-36N-WGS84 projection, mosaicked and cropped to study area boundary, and resampled to 250m resolution using the MODIS MRT Reprojection Tool provided by NASA, LPDAAC. The resampling method used was the nearest neighbor to not alter the original pixel data values.

An important and critical step in the preprocessing stage of the data is to remove all pixels that contain cloud, cloud shadows, high aerosol loading, dead or noisy detectors, or missing data. All MODIS products are packed with science data sets that include quality assurance data both for data state and reflectance bands quality. The quality assurance data are loaded per pixel and converted to binary form and are then interpreted based on the QA MODIS science data set manual. Only pixels meeting the above mentioned criteria are considered for calculations. The bit-packing process was performed in Python using libraries from Pymasker tool available as open source from Github. Figure 2 below shows an example for data mask created for tile MOD09A1.2000233.hdf.

2.4.Calculating MrVBF Index:

The Shuttle Radar Topography Mission SRTM 1 arc second (approximately 30m resolution) DEM has been recently released for the tropical regions all around the world including our study area. The SRTM 1" DEM is considered a more detailed and superior product to the famously known SRTM 3" (approximately 90m resolution) as the latter is either subsampled or averaged form the first. SRTM 1" data are distributed by LPDAAC into tiles each covers an area of 1^o X 1^o. Tiles covering the study area are downloaded and merged using GIS software package.

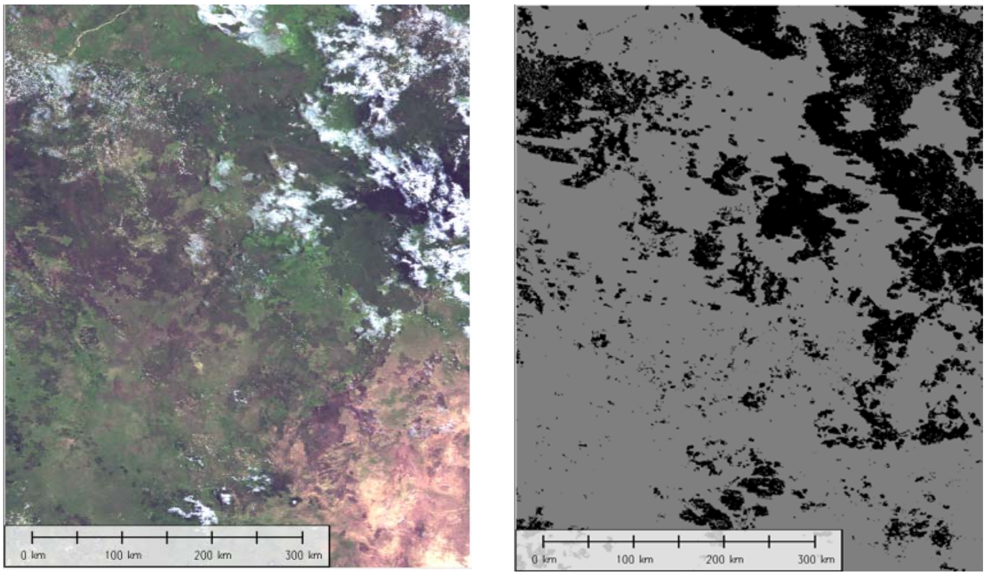


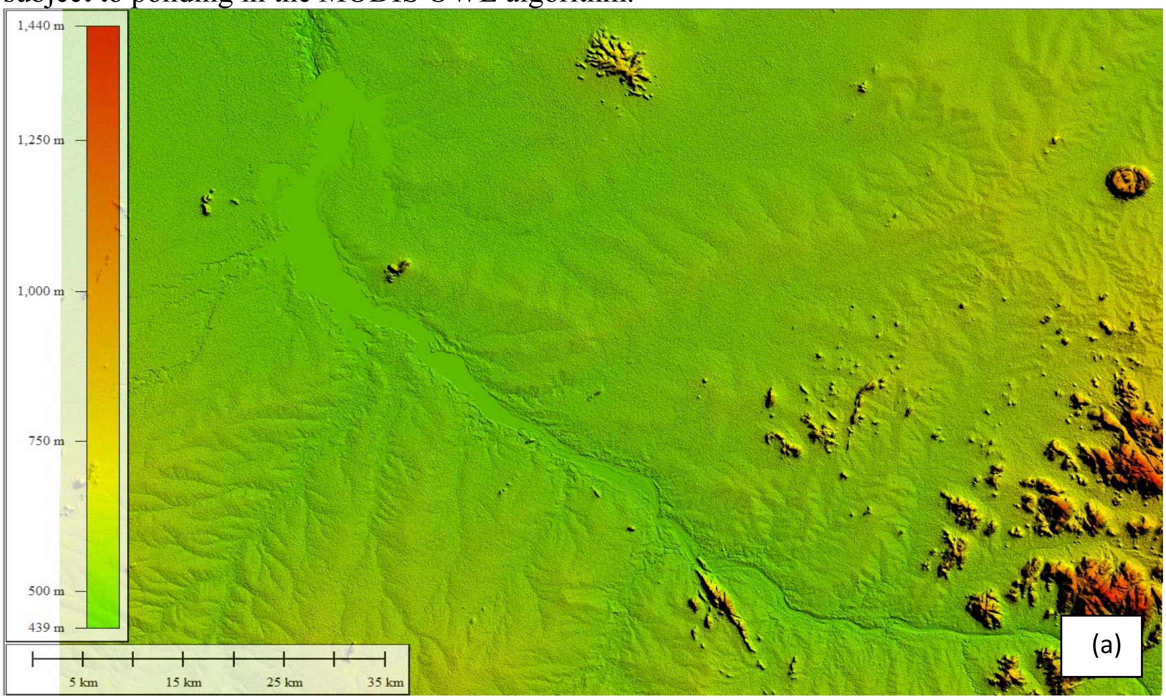
Figure 2: (a) Original RGB (1:4:3) composite for tile MOD09A1.2000233.hdf, and (b) The created data mask where black color denotes the excluded pixels from the calculations

The MrVBF index has been calculated using the System for Automated Geoscientific Analyses SAGA; a free open source GIS tools that is widely used by the GIS and remote

sensing research community. The SRTM 1” DEM is input to the model while setting the default values for all other parameters as in the Table 2 below (Guershmann, 2011). The index has been calculated at 1” resolution first and is then resampled to 250m resolution to match that of the MOD/MYD09A1 resampled products.
Table 2: Parameters for calculating MrVBF

Parameter	**Range**	**Default Value**
Initial Threshold for Slope	0 – 100	16
Threshold for Elevation Percentile (Lowness)	0 - 1.0	0.4
Threshold for Elevation Percentile (Upness)	0 – 1.0	0.35
Shape Parameter for Slope	NA	4.0
Shape Parameter for Elevation Percentile	NA	3.0
Maximum resolution as percentage of the diameter of the DEM.	0 – 100	100

Figure 3 below shows the merged SRTM 1” DEM and the calculated MrVBF values for the study area. It is clear that flat areas hold higher values of MrVBF and this makes them more subject to ponding in the MODIS OWL algorithm.



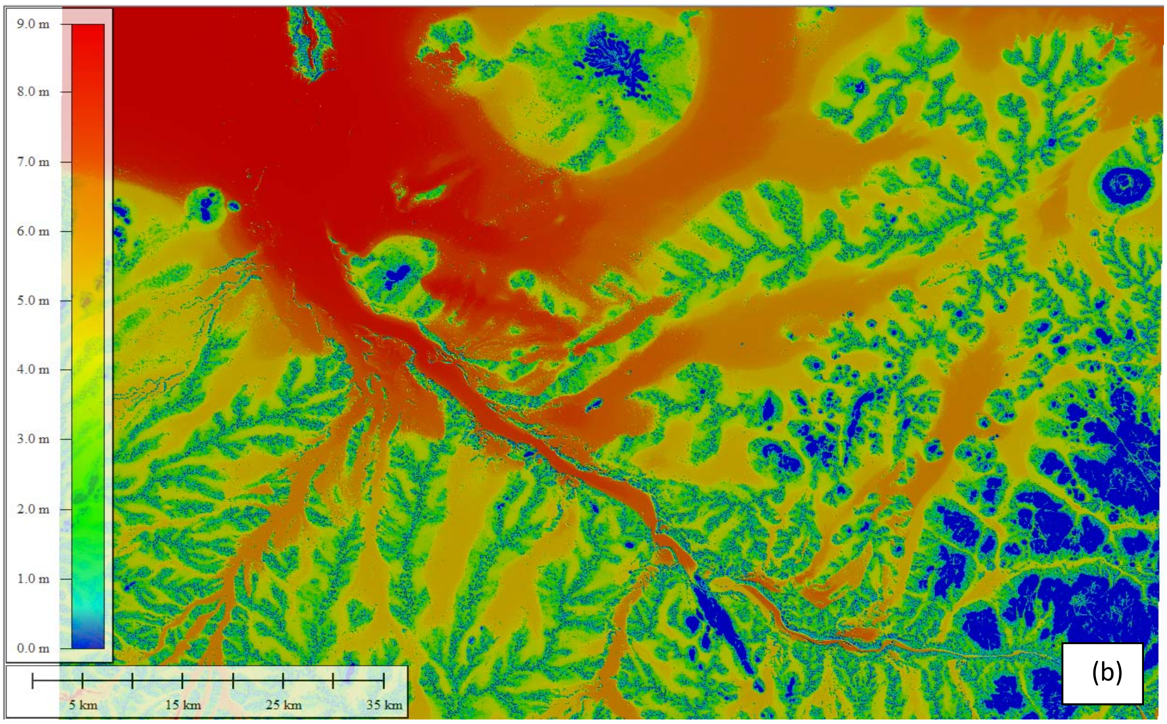


Figure 3: (a) SRTM 1"DEM and (b) Calculated MrVBF values resampled at 250m

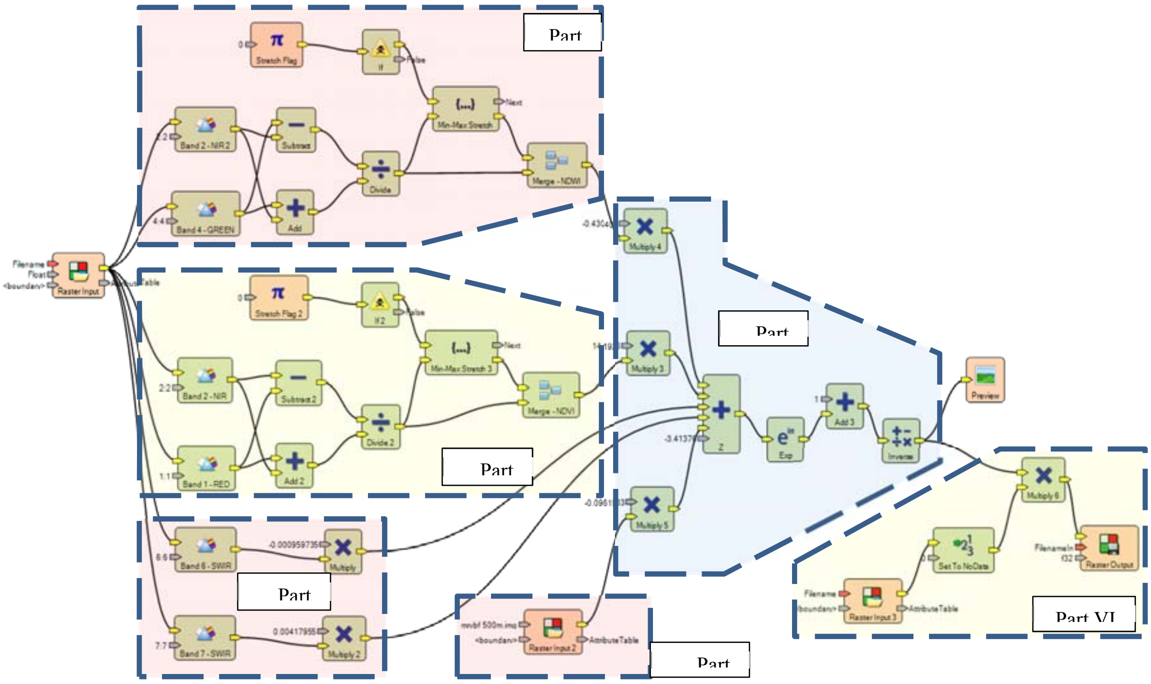


Figure 4: Spatial Model for Calculating MODIS OWL

2.5.Calculating MODIS OWL:

After masking only the valid MODIS pixels and calculating the MrVBF values, ERDAS Imagine (version 2013) image processing software is used to calculate the MODIS OWL as in equations 1 through 3. The MODIS OWL is not included inside the spectral indices under the unsupervised classification module of ERDAS Imagine. As such, the spatial model editor has been used to create a workflow to calculate the MODIS OWL inside ERDAS Imagine. Figure 4 shows a schematic of the spatial model used to calculate MODIS OWL inside ERDAS Imagine.
The spatial model is divided into 6 parts as follows:

- First, the raster file is loaded into the model through the raster input operator.
- In part I the NDWI index is calculated by using bands 2 and 6 of the loaded image. The NDWI is also checked not to have outliers and is always between -1 and +1,
- Similarly, in part II, the NDVI is calculated using bands 1 and 2 of the loaded image and the output is also checked to be within the -1 to +1 range.
- In parts III and IV, the SWIR bands (6 and 7) and the MrVBF index are loaded to the model.
- In Part V the water fraction is calculated by applying equation 1, and finally
- In part VI the data is masked by the quality assurance mask previously created by Pymasker. Pixels that are to be excluded due to quality issues are given a "NO DATA" value in the output raster to discriminate it from other pixels.
- The output raster is containing the MODIS OWL water fraction for each pixel is then saved in a new file.

All the above should be repeated for all 682 downloaded scenes of MOD09A1 and all 553 scenes for MYD09A1. The process has to be automated. Starting ERDAS Imagine version 2013, it is possible to create and execute a spatial model within a python scripting language (Python Scripting with ERDAS Imaging Spatial Modeler, Intergraph). A python script is written to calculate the run the MODIS OWL spatial model in a batch mode for all scenes and automatically saves the output raster files. The script uses ERDAS Imagine Spatial Modeler libraries to load the model, prepare its input data, and write its output. The python script is combined with the script that creates the data mask to save time loading the images. The output raster files still contain areas of NODATA after applying the data quality assurance mask. The following section discusses how to fill in many of the NODATA cells in MOD products with MYD data and how to interpolate and fill the rest.

2.6.Creating a combined product and gap filling:

As discussed earlier, one of the major challenges that hinder the use of data from optical sensors in flood plain delineation is cloud cover. In order to overcome this limitation, the following procedure is adopted in this study:

- MODIS OWL is calculated for all downloaded tiles from both the Aqua and Terra platforms, each has its own data mask and NODATA cells as discussed in the previous section. Values calculated from the Terra platform files shall be named MOD09OWL and those calculated from Aqua platform file shall be named MYD09OWL.

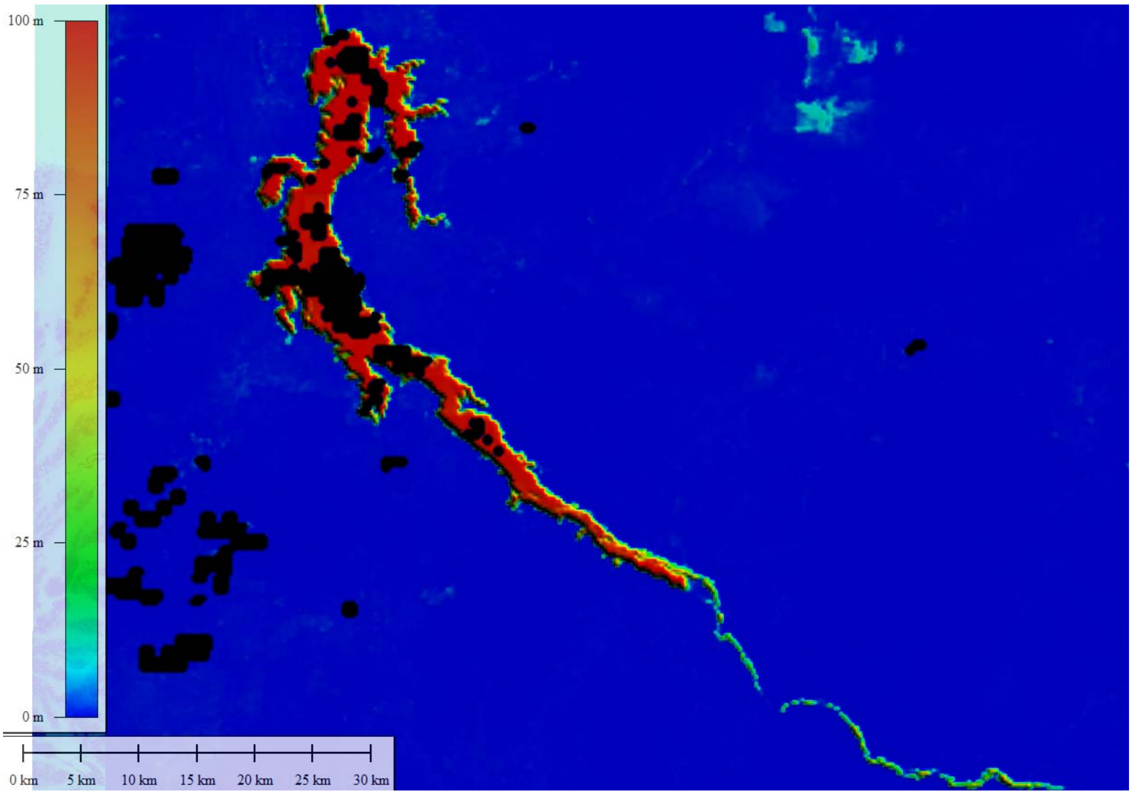


Figure 5: Calculated MCDOWL for tile A2003273.hdf

- Since both Terra and Aqua platforms acquire images for the study area at different times (10:00am and 2:00pm respectively) everyday; and since we are also using the 8-day composite products of each platform (MOD/MYD09A1) in the calculations; then there is a large chance that pixels marked as "NODATA" in the 8-day composite of the Terra platform will contain valid readings in the 8-day composite of the Aqua platform.
- It is decided to create a combined product of Aqua and Terra platforms for the calculated values of OWL. NODATA cells in MOD09OWL are replaced with respective values from their MYD09OWL counterpart whenever applicable. The combined product shall be named MCD09OWL. Ticehurst et al, 2014 and Guerschman et al, 2011 followed a similar procedure using the MODIS daily products MOD/MYD09GA.

The average cloud cover percentage in the MOD and MYD products are 13.08% and 20.86% respectively. After creating the combined product, the average cloud cover decreased to 7.52% and the great thing is that gaps are filled with true observations. Figure 5 below compares the cloud cover percentage for the three products for 1800 days starting Feb-2000.

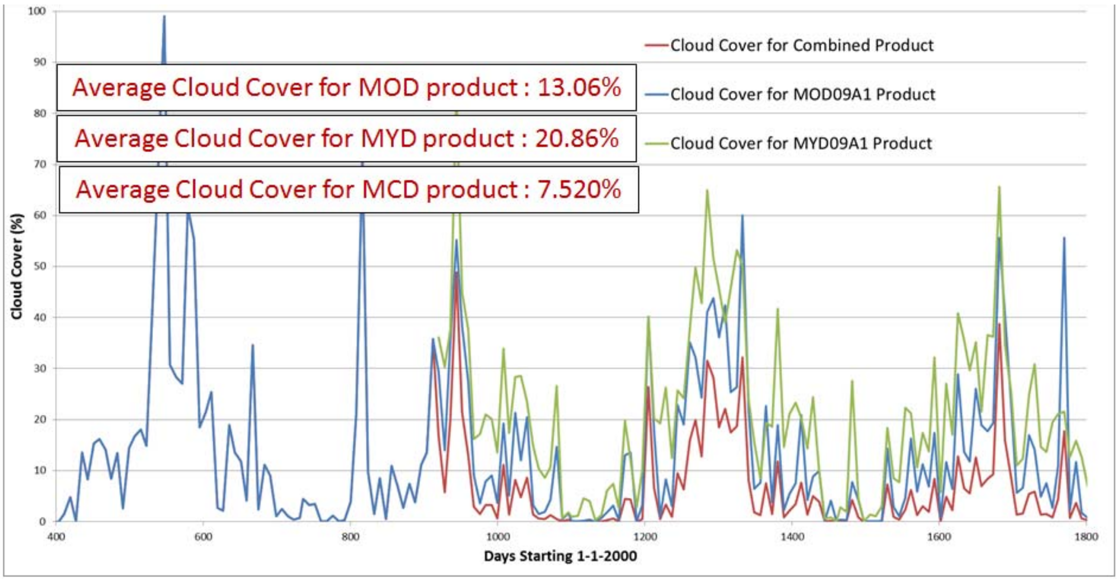


Figure 6: Average Cloud Cover Percentage

As shown in figure 6, the cloud cover is concentrated during the rainy season especially during the rising stage of flood where maximum inundation of water is expected. The combined MCDOWL product still contains significant areas (up to 50% of the scene) covered by clouds that need to be filled.

Weiss et al, 2014 developed a new gap filling algorithm that can be used to fill in large continuous patches of missing data and is optimized for use in time series applications. The method was also developed and tested on MODIS data on continental scale that makes the method suitable for our application. The method succeeded in filling large gaps over Africa with R^2 of more than 0.87 (Weiss et al., 2014). The method works as follows:

- The method depends on calculating mean raster for all the time series
- Calculates, for each gap cell, an average of the ratios between valid values of neighboring cells in the current image and the mean raster (N_{to} / N_{mean}).
- The average ratio is multiplied by the mean value of the gap cell itself (G_{mean}) to get the fill value F as in equation 4 below.
- The current fill value is used to fill the next cell
- This is done in 8 passes and the median is then calculated
- A python code has been written to automate the process of creating the combined product and gap filling

$$F = \frac{\sum_{1 \ldots n}\left(G_{mean} \times \frac{N_{t0}}{N_{mean}}\right)}{n} \quad \text{Eq. (4)}$$

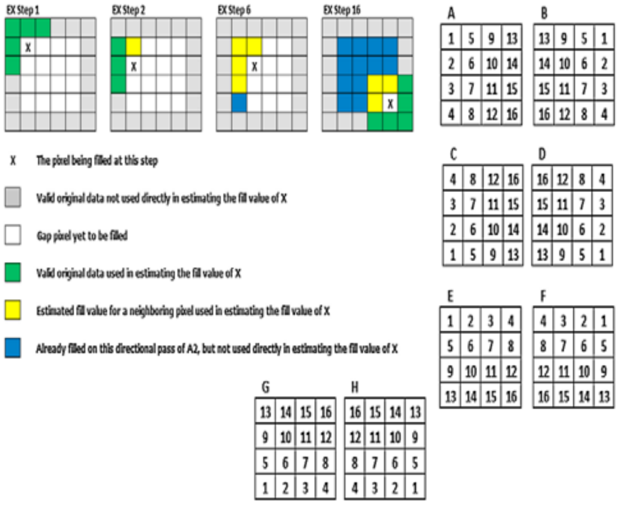


Figure 7: Gap filling Algorithm after Weiss et al., 2014

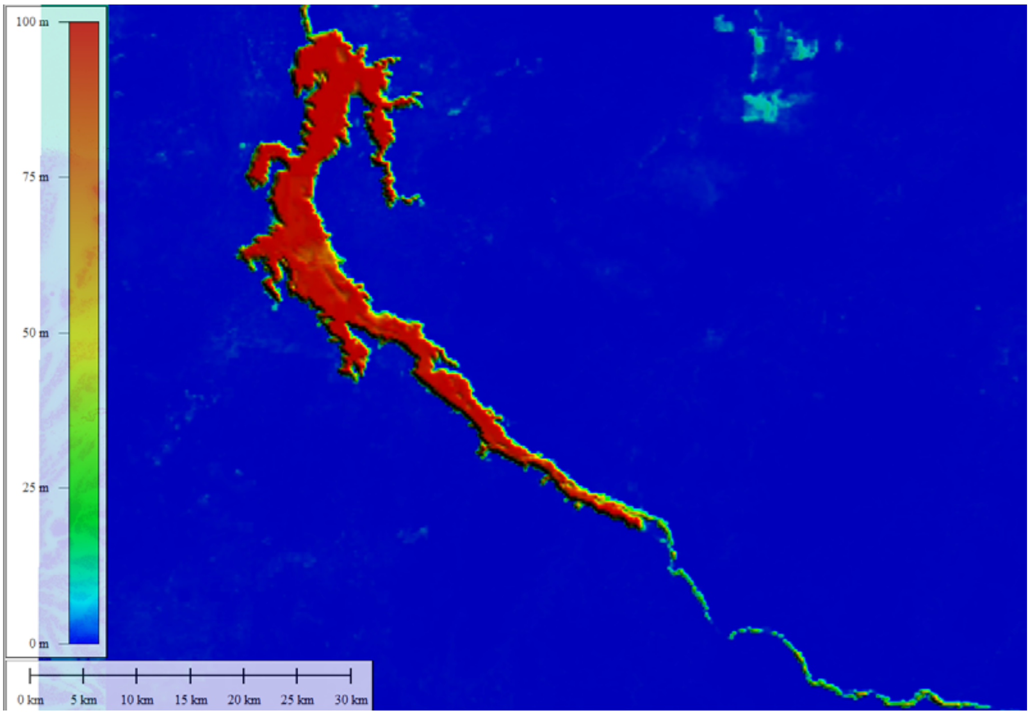


Figure 8: Gapfilled Combined MCDOWL for tile A2003273.hdf

2.7.Calibration and Verification:

In order to convert the MODIS OWL water fraction maps to water - non water thematic maps, we need to determine the threshold value (percentage) above which a pixel is considered to be wet. The threshold value is usually determined using ground survey data of areas that are known to be water bodies. These surveyed patches (ground truth data) should be laid over the MODIS OWL maps and the optimum water fraction percentage could be found that yields the surveyed wet areas as wet. This process should be repeated over the dry and wet season due to different characteristics of wet pixels all the year round.

Due to lack of field data and limited accessibility, ground truth data are not available for the study area to help calibrating the MODIS OWL method to identify water bodies. Instead, high resolution satellite images shall be used to determine the wet areas at specific time stamps and these images shall act as ground truth data. Ticehurst et al., 2013 used higher spatial resolution Landsat data as "ground truth" for assessing how well the MODIS products could map flood extent in the lower Balonne floodplain, Fitzroy River and Macquarie Marshes during a flood event. Also, Guerchmann et al, 2011 used water maps calculated from Landsat data to count and calculate the water fraction in a MODIS pixel.

In this study, Landsat data is chosen to provide ground truth data for MODIS OWL as Landsat forms the most consistent dataset that covers all the downloaded tiles since year 2000 till today and it has been used extensively in the literature for detecting water bodies. The procedure is summarized as follows:

- Landsat and MODIS images for the study area are selected carefully to have similar acquisition times (as much as possible) and to have common cloud free areas.
- MODIS data are available 2 times daily (from both platforms) while Landsat revisit time is 8-16 days. Daily MODIS surface reflectance products (MOD/MYD09GA) are used in the verification process instead of the 8-day composites in order to match acquisition times more accurately.
- Landsat 7 ETM+ data after May, 2003 are avoided in the selection process due to the failure of Scan Line Corrector (SLC). Images with SLC turned off have many missing data pixels that shall degrade the calibration process.
- Due to MODIS swath distribution and orbit schedule with respect to Landsat 8 orbit, same day coverage of both daily MODIS and Landsat 8 is not available for the study area. As such, averaging of the previous and the following day MODIS scenes are considered in the calibration.
- MODIS OWL is calculated for the selected daily MOD/MYD09GA scenes in the same way as has been done with the 8-day composites before.
- Water maps are calculated from Landsat image using the Modified Normalized Difference Water Index (mNDWI) developed by Xu et al, 2006. Pixels having values more than -0.1 are considered wet (Ticehurst, 2015).
- MODIS images are then geo-referenced accurately to the Landsat water maps.
- For each Landsat / MODIS pair, a threshold value is iteratively applied to the MODIS OWL water fraction (masking pixels with values higher than that threshold as water), and agreement with the respective Landsat map is calculated in terms of kappa statistics (Landis and Koch, 1977). Several values for the water fraction threshold are applied till reaching the value that provides maximum agreement (highest kappa value) with Landsat water maps.

- The above process shall be repeated over several selected pairs of Landsat/MODIS scenes covering the dry and wet season and an overall average of the water fraction threshold that provides the best agreement is calculated.
- The calculated threshold is then applied to the combined MODIS OWL scenes to get water maps of the study area.

Tables 3 below shows the image pairs used in the verification process along with their acquisition time and optimum kappa statistic value. It is found that the maximum agreement between Landsat and MODIS scenes occurs at OWL threshold of 20%. The best agreement varies between 0.751 and 0.916 which is considered substantial to strong agreement (Landis and Koch, 1979). The optimum OWL threshold is almost constant between the dry and wet seasons. Figure 9 shows the agreement between Landsat and MODIS scenes for pair 3.

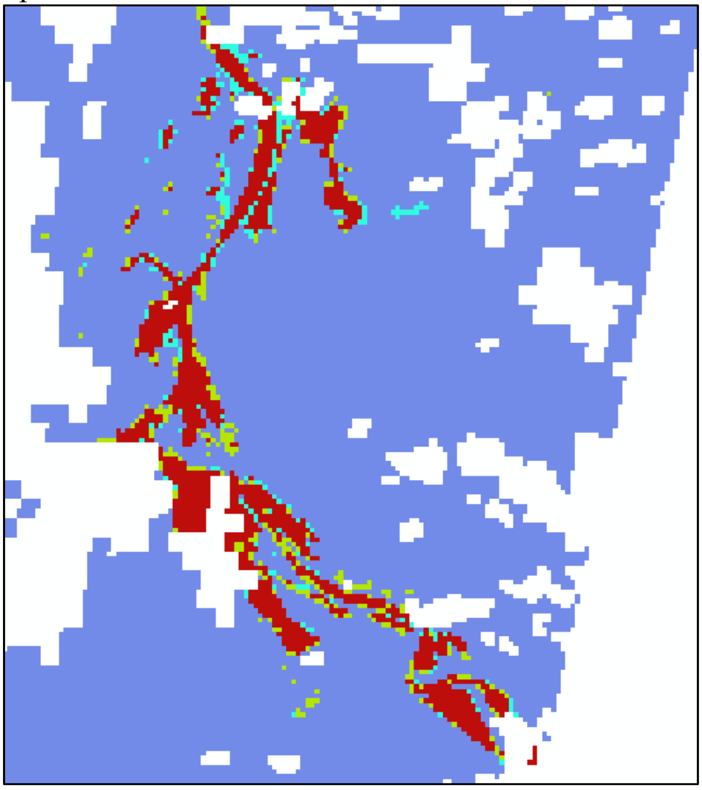


Figure 9: Agreement for Pair 3. Red color represents pixels that are considered wet in both Landsat and MODIS images and Blue represents pixels that are considered dry in both scenes. Green represents pixels that are considered wet in Landsat scene only, while Cyan represents pixels that are considered wet only in MODIS scene. White represents missing data due to cloud cover.

Table 3: Verification and Kappa Statistics

Pair No.	Landsat		MODIS		Kappa
	Scene ID	Date	Scene ID	Date	

Pair No.	Landsat		MODIS		Kappa
	Scene ID	Date	Scene ID	Date	
1	LE7171052-2000281 (Landsat7)	7-10-2000 7:48am	MOD09GA.A2000281.h21v07 (TERRA) MOD09GQ.A2000281.h21v07 (TERRA)	7-10-2000 10:30am	0.88
2	LE71720522002357 (Landsat7)	22-12-2002 7:52am	MOD09GA.A2002357.h21v07 (TERRA) MOD09GQ.A2002357.h21v07 (TERRA) MYD09GA.A2002357.h21v07 (AQUA) MYD09GQ.A2002357.h21v07 (AQUA)	22-12-2002 10:30am 22-12-2002 2:00pm	0.916
3	LC81720522014222 (Landsat8)	10-8-2014 8:04am	MOD09GA.A2014221.h21v07 (TERRA) MOD09GQ.A2014221.h21v07 (TERRA) MYD09GA.A2014221.h21v07 (AQUA) MYD09GQ.A2014221.h21v07 (AQUA) MOD09GA.A2014223.h21v07(TERRA) MOD09GQ.A2014223.h21v07 (TERRA) MYD09GA.A2014223.h21v07 (AQUA) MYD09GQ.A2014223.h21v07 (AQUA)	9-8-2014 10:30am 9-8-2014 2:00pm 11-8-2014 10:30am 11-8-2014	0.751

Pair No.	Landsat		MODIS		Kappa
	Scene ID	Date	Scene ID	Date	
				2:00pm	

3. Results:

The developed workflow succeeded in generating water fraction maps without gaps for the study area for almost 5 years starting Feb 2000 till Dec 2014. MODIS OWL algorithm proved high efficiency in detecting water bodies under mixed inundation. The Roseires reservoir gets almost dry in June and reaches its maximum inundation in October almost each year. The MODIS OWL algorithm succeeded in detecting variation in water inundation all the year round providing maximum separation between water bodies and the surroundings. Figure 10 shows the mean raster of selected days at mid of January, March, June, August, October, and December for the period from Feb-2000 till Dec-2011 (before heightening of the Dam) while Figure 11 shows the mean raster for the same days but for the period from Jan 2012 till Dec-2014. The effect of heightening the Dam is clearly demonstrated.

Water fraction maps are then converted to thematic water maps by applying the optimum threshold of 20% where pixels having water fraction more than 20% are considered as inundated. Reservoir surface area can be calculated from the water maps for the whole time series. The variation of reservoir area with time for the period from Jan-3003 till Dec-2007 is available from the Nile DSS database. Reservoir area calculated from the developed algorithm show very high agreement with the measured areas as seen from Figure 12.

It is clear that both actual measurements and calculated areas agree to a great extent during the rising stage of the flood and they almost reach the same peak inundation extent. However, during the dry period, the agreement notably decreases. This is because there are areas and patches that remain wet during the dry season that are not connected to the reservoir outlet (Figure 13). These areas are already deducted from the reservoir rating curve according to the Nile DSS database (considered as dead storage). This explains why areas extracted from the MODIS OWL algorithm are larger than measurements during the dry season.

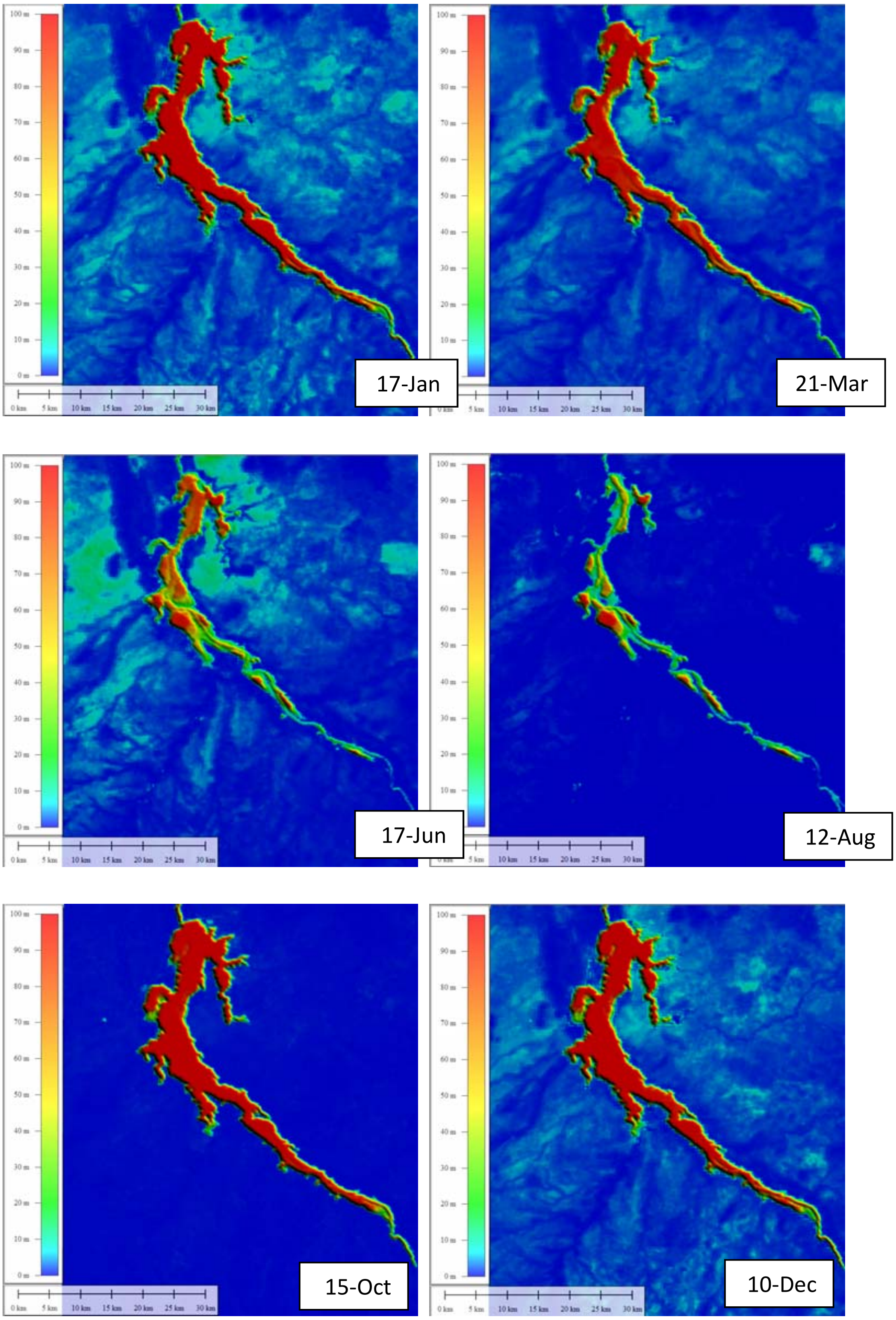
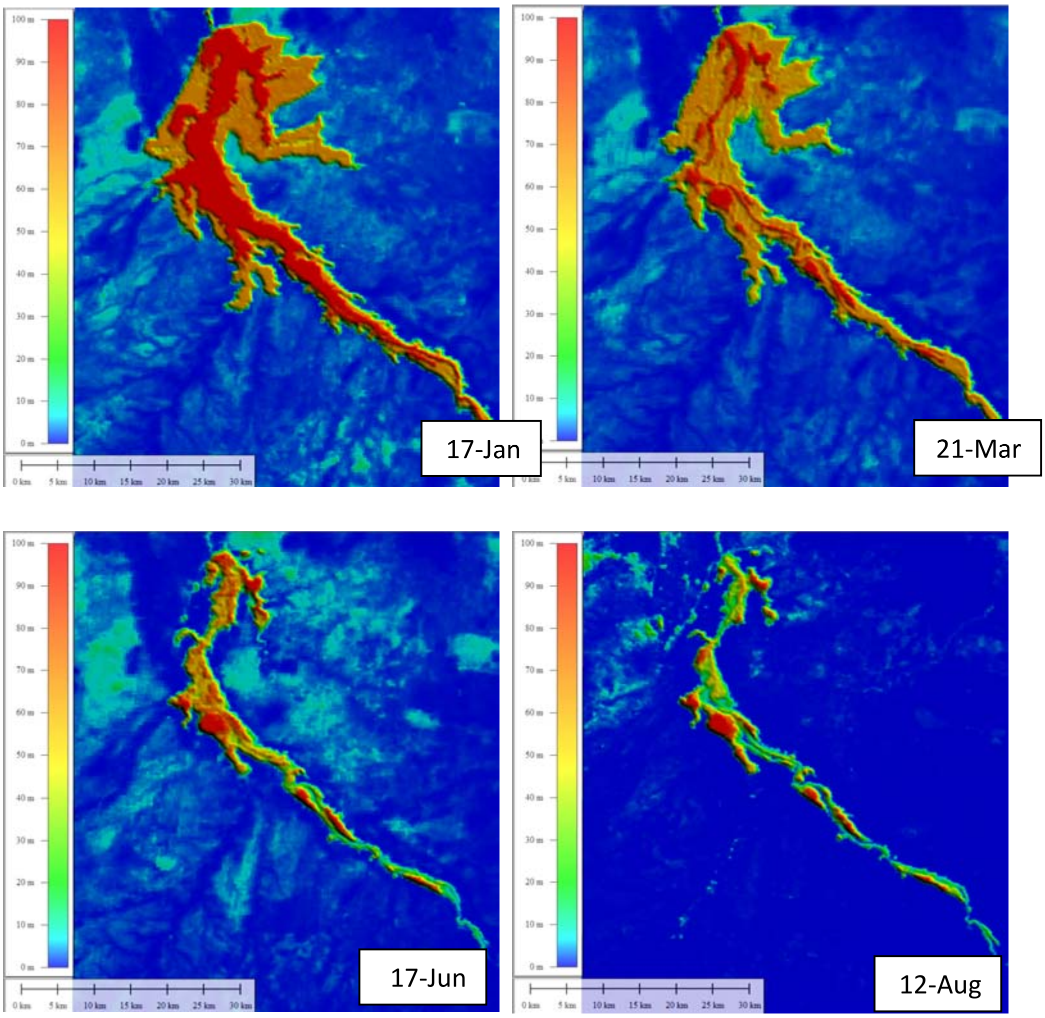

17-Jan
21-Mar
17-Jun
12-Aug
15-Oct
10-Dec

Figure 10: Mean Raster for OWL water fraction (2000-2011)



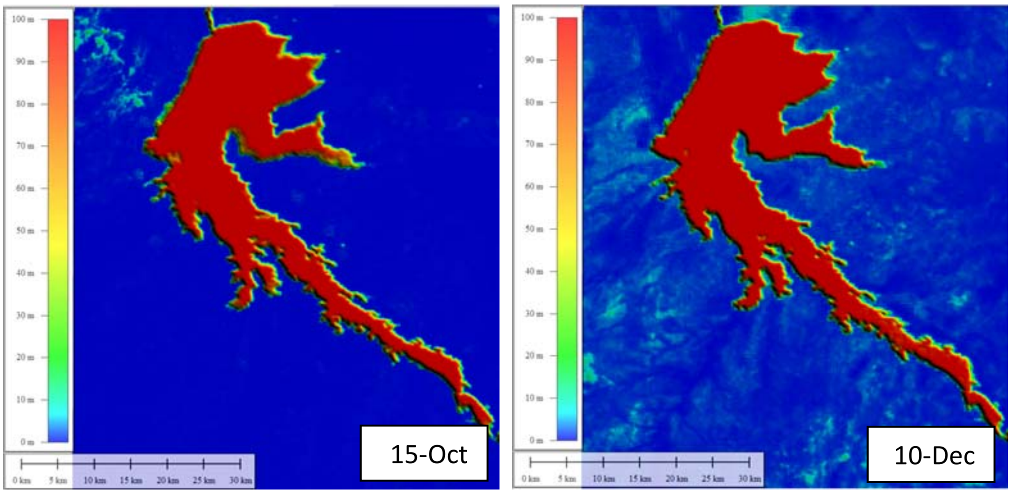


Figure 11: Mean Raster for OWL water fraction (2012-2014)

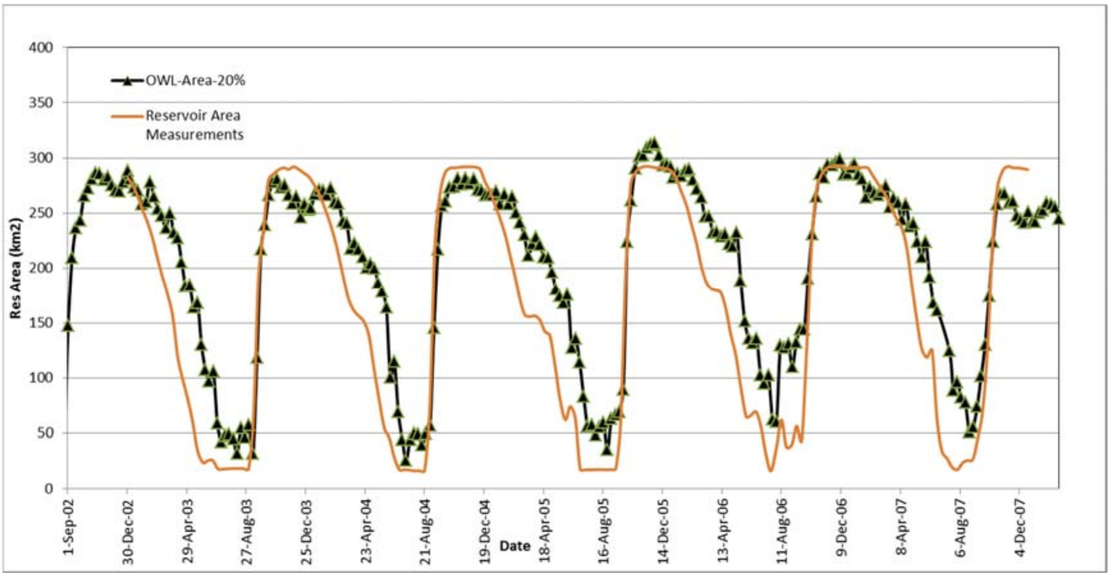


Figure 12: Comparison between Extracted Reservoir Area from applying the new methodology using OWL threshold at 20% and actual measurements for the period from 2003-2007.

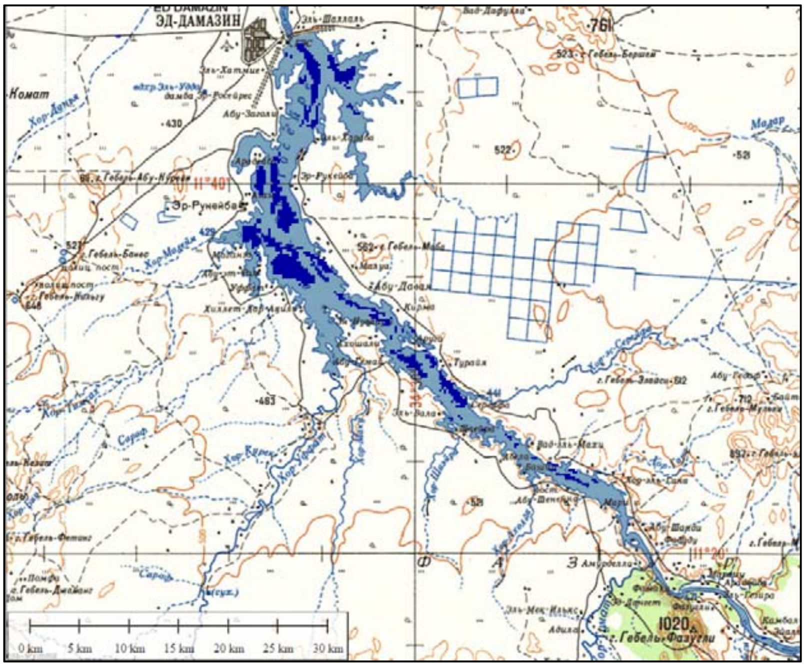


Figure 13: Thematic water map for the Roseires Reservoir on 12-8-2003 shows disconnected patches of inundated areas during the dry season. Water presented as deep blue over the background map.

After heightening the Dam in 2012, the extracted reservoir areas are highly increased as in Figure 14 below. The area reached almost 650 square kilometers its maximum inundation.

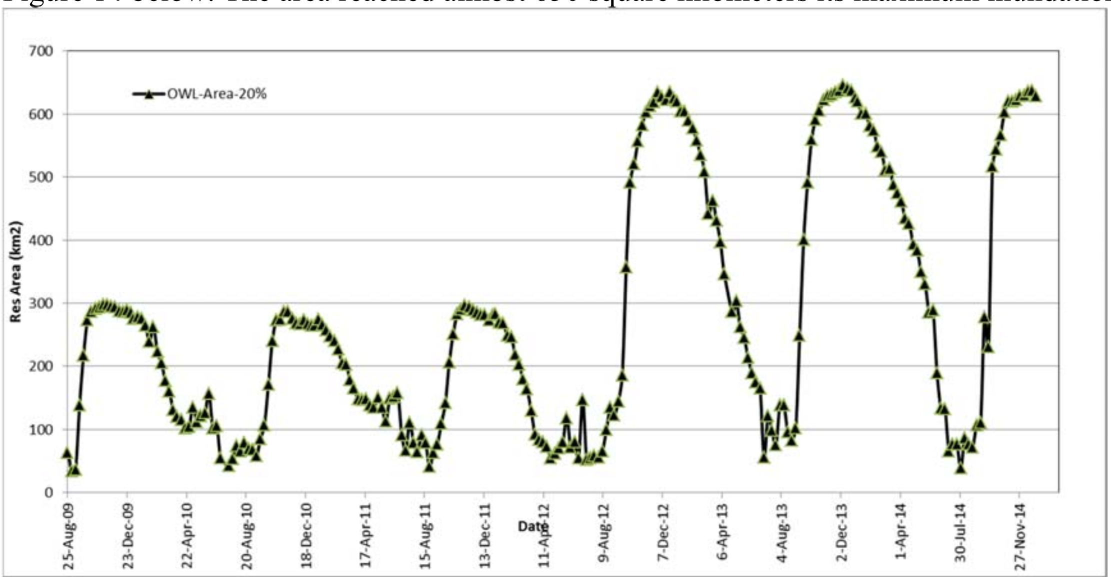


Figure 14: Extracted Reservoir Area from applying the new methodology using OWL threshold at 20% for the period from 2009-2014.

4. Conclusions:

The developed methodology proved to be very effective in mapping water bodies under mixed inundation. The methodology used the MODIS OWL technique for calculating water fraction in each pixel and it proved to provide maximum separation between inundated pixels and the surroundings. Cloud cover; which is considered one of the greatest challenges that limits using remote sensing data in tropical regions, is overcome by creating a combined product from two MODIS platforms and using a robust gap filling technique to fill the remaining gaps in data with a relative high accuracy. The workflow; once calibrated; is fully automated and require minimum human input. The developed workflow succeeded in creating consistent spatial and temporal maps when applied to the Roseires reservoir. The generated water maps matched the ground measurements to a great extent besides having a temporal frequency of 8-days which enables close monitoring to water bodies. The workflow need to be tested and applied on seasonal wetlands in future studies.

5. References:

1. Brakenridge, R., and Anderson, E. (2006). MODIS-based flood detection, mapping and measurement: The potential for operational hydrological Applications. Transboundary Floods: Reducing the Risks through Flood Management, 72:1-12.
2. Chen, Y., Huang, C., Ticehurst, C., Merrin, L., Thew, P. (2013). An evaluation of MODIS daily and 8-day composite products for floodplain and wetland inundation mapping. Wetlands, 33:823-835.
3. Doble, R.; Crosbie, R.; Peeters, L.; Joehnk, K.; Ticehurst, C. Modelling overbank flood recharge at a continential scale. Hydrol. Earth Syst. Sci. 2014, 18, 1273–1288
4. Guerschman, J.P., Warren, G., Byrne, G., Lymburner, L., Mueller, N., and Van-Dijk, A. (2011). MODISbased standing water detection for flood and large reservoir mapping: algorithm development and applications for the Australian continent. CSIRO: Water for a Healthy Country National Research Flagship Report, Canberra.
5. Gao, B.C. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens. Environ. 1996, 58, 257–266
6. Gallant, J.C. and Dowling, T.I. (2003) A multiresolution index of valley bottom flatness for mapping depositional areas. Water Resour. Res. 39, 1347.
7. H.U. Neue, J.L. Gaunt, Z.P. Wang, P. Becker-Heidmann, C. Quijano, Carbon in tropical wetlands, Geoderma, Volume 79, Issue 1, 1997, Pages 163-185, ISSN 0016-7061, http://dx.doi.org/10.1016/S0016-7061(97)00041-4.
8. Karim, F., Dutta, D., Marvanek, S., Ticehurst, C., Petheram, C. (2013). Hydrodynamic Modelling of Potential Impacts of Climate Change on Hydrological Connectivity of Floodplain Wetland, Proceedings of the 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1 – 6 December 2013.
9. Landis, J. R. and Koch, G. G. (1977), The measurement of observer agreement for categorical data. Biometrics 33, 159-174

10. McFeeters, S.K., (1996). The use of normalized difference water index (NDWI) in the delineation of open water features. International Journal of Remote Sensing, 17:1425-1432.
11. Ralph W. Tiner, Megan W. Lang, Victor V. Klemas, Remote Sensing of Wetlands; Applications and Advances, CRC Press, Taylor & Francis Group, 2015
12. The Kyoto and Carbon initiative, Jaxa, Japan, 2009
13. Ticehurst, C.J., Chen, Y., Karim, F., Dutta, D., Gouweleeuw, B. (2013) Using MODIS for mapping flood events for use in hydrological and hydrodynamic models: Experiences so far. In Proceedings of MODSIM2013, 20th International Congress on Modelling and Simulation, Adelaide, Australia, 1 – 6 December 2013.
14. Ticehurst, C., Guerschman, J.P., Chen, Y. (2014). The strengths and limitations in using the daily MODIS Open Water Likelihood algorithm for identifying flood events. Remote Sensing, 6:11791-11809, DOI:10.3390/rs61211791.
15. Ticehurst, C.J., Dutta, D., Fazlul, K., Petheram, C., Guerschman, J.P. (2015). Improving the accuracy of daily MODIS OWL flood inundation mapping using hydrodynamic modelling. Natural Hazards, 78:803–820.
16. Ward, D.P.; Hamilton, S.K.; Jardine, T.D.; Pettit, N.E.; Tews, E.K.; Olley, J.M.; Bunn, S.E. Assessing the seasonal dynamics of inundation, turbidity, and aquatic vegetation in the Australian wet-dry tropics using optical remote sensing. Ecohydrology 2013, 6, 312–323
17. Weiss, D. J.; Crabtree, R.L. Percent surface water estimation for MODIS BRDF 16-day image composites. Remote Sens. Environ. 2011, 115, 2035–2046
18. Weiss, D. J., Peter M. Atkinson, Samir Bhatt, Bonnie Mappin, Simon I. Hay, Peter W. Gething, An effective approach for gap-filling continental scale remotely sensed time-series, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 98, December 2014, Pages 106-118, ISSN 0924-2716, http://dx.doi.org/10.1016/j.isprsjprs.2014.10.001.
19. Xu, H. (2006). Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. International Journal of Remote Sensing, 27(14): 3025-3033.