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A review of applications of satellite SAR, optical, altimetry and DEM data for surface water modelling, mapping and parameter estimation

Z. N. Musa[1], **I. Popescu**[1], **and A. Mynett**[1,2]

[1]UNESCO-IHE Institute for Water Education, Delft, the Netherlands
[2]Department of Civil Engineering, Technical University Delft, the Netherlands

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Correspondence to: Z. N. Musa (z.musa@unesco-ihe.org)

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Abstract

Hydrological data collection requires deployment of physical infrastructure like rain gauges, water level gauges, as well as use of expensive equipment like echo sounders. Many countries around the world have recorded a decrease in deployment of physical infrastructure for hydrological measurements; developing countries especially have less of this infrastructure and where they exist, they are poorly maintained. Satellite remote sensing can bridge this gap, and has been applied by hydrologists over the years, with the earliest applications in water body and flood mapping. With the availability of more optical satellites with relatively low temporal resolutions globally, satellite data is commonly used for: mapping of water bodies, testing of inundation models, precipitation monitoring, and mapping of flood extent. Use of satellite data to estimate hydrological parameters continues to increase due to use of better sensors, improvement in knowledge of/and utilization of satellite data, and expansion of research topics. A review of applications of satellite remote sensing in surface water modelling, mapping and estimation is presented, and its limitations for surface water applications are also discussed.

1 Introduction

Hydrological data collection still remains a difficult task nowadays due to none availability of measurement devices, inaccessibility of the terrain and limitations of space/time (Pereira-Cardenal et al., 2011). A good alternative to overcome these difficulties is use of satellite remote sensing, which can give a synoptic view of target areas (Fig. 1), measure target surface changes and therefore provide information needed for hydrological studies, river basin management, water hazard/disaster monitoring/prevention and water management, etc. Through the science of remote sensing, information about an object can be obtained without coming in direct contact with it (Lillesand et al., 2004). This capability works by measuring electromagnetic energy reflected or radiated from

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objects on the earth's surface (Fig. 1), in such a way that the difference in reflectivity of objects enables recognition/detection and isolation of each type/class.

Remotely sensed data are of two types depending on the main source of energy. Passive remote sensing depends on natural energy from the sun. Active remote sensing uses controlled energy sources from instruments beaming sections of the electromagnetic spectrum. Imagery obtained via instruments that measure reflectance from the sun, are known as optical imagery. Optical imagery from satellites is therefore acquired during the day since it depends on the reflections of sunlight from objects on the earth surface in the absence of cloud cover. The optical satellites are in near earth orbits and are therefore able to provide detailed data at high ground resolution (e.g. Fig. 1); although the best resolution data are usually not freely available and expensive to obtain. Due to this detailed resolution, optical satellite imagery is used for inundation mapping, drainage mapping, disaster monitoring, land-use/land cover change analysis etc. (Owe et al., 2001).

Active remote sensing can provide data as imagery (e.g. Synthetic Aperture Radar, SAR), and in the form of pulse measurements (e.g. altimeters and scatterometers). Radar is an active source of remote sensing data which acquires data via instruments that emit radar signal towards the object of interest and measure the reflected energy from the object. Radar can penetrate cloud cover and can be acquired at any time independent of availability of sunlight. The penetration characteristic of the SAR satellites enables measurement of soil moisture in bare areas, making it useful for land-use and land cover studies as well as earth observation and monitoring (Owe et al., 2001). For water bodies the reflectivity of radar waves is spectacular giving a very low radar return and very dark images. However when there are surrounding or emergent vegetation, wind, turbulence etc, there can be significant backscatter; which affects the accuracy of information obtained from the radar measurements (Smith, 1997).

Satellite remote sensing has been applied in hydrology for many years. A review by Smith (1997) shows that the earliest applications were water body and flood mapping; the review includes many examples of inundation maps developed from satellite

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imagery. Owe et al. (2001) also compiled papers presented at a conference on applications of remote sensing in many aspects of hydrology.

The main scope of this review is to present literature findings about application of satellite remote sensing in surface water modelling, mapping and parameter estimation. The review limits itself to water flowing within channels, coastal areas, and therefore excludes applications of satellite remote sensing for rainfall estimation, rainfall/run off modelling and its associated routing estimations.

The paper is structured into two main parts. The first covers the applications of SAR, Optical, Altimetry and DEM data for estimation of surface water parameters, modelling and mapping. The second part discusses the limitations of utilizing satellite derived data in surface water applications. The review ends with a conclusion.

2 Satellite data applications for surface water studies

Water reflects electromagnetic waves differently depending on its contents; pure clear water reflects differently from muddy water or water containing vegetation (floating or submerged). The amount of energy measured from the satellite sensor also depends on the bands used; blue band penetrates water up to 10 m, red band is partially absorbed, and near infra-red band is totally absorbed. These sensor properties consequently affect the image, so that an image acquired using the blue band will measure reflectance from any submerged vegetation within its reach, while red/near infra-red images will show water as dark grey/black respectively (Meijerink et al., 2007).

2.1 SAR data applications

SAR data are useful for flood extent measurements even in cloud covered areas, and are therefore often used to make flood maps (e.g. Vermeulen et al., 2005; Horritt, 2006; Mason et al., 2007; Schumann et al., 2007; Di Baldassare et al., 2009).

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To utilise SAR data for flood depth estimation, methods have been developed that derive flood heights from flood extent data. The methods used combine SAR data with elevation data sources like DEMs, altimetry, and TINs. Mason et al. (2007) and Schumann et al. (2006), estimated the mean cross sectional water levels used for model evaluation from the intersection of SAR flood extent boundaries with LIDAR DEM. Schumann et al. (2006) used linear regression and an elevation based model (REFIX) to convert SAR flood extend to heights and derived the flood water depth. The result showed an RMSE of 18 cm for a channel with no hydraulic structures and 31 cm for a channel with many hydraulic structures and changes in slope. The study recommends that nonlinear regression/piece wise regression can be used in the case of sudden changes in slope (due to hydraulic structures etc.) that cause the channel geometry to change.

The advantage of phase changes in SAR interferometer data (INSAR) enables detection of change in the Earths land-use and land cover. This characteristic is very useful for identification of flooded areas over wetlands and has been used to calculate the changes in water levels using satellite altimetry data for calibration (Kim et al., 2009; Jung et al., 2010). Interferometric phase difference between two SAR images is called the interferogram and includes signatures from topography, noise, displacement, atmospheric effects and baseline error. To obtain the displacement phase used to obtain the change in water height, all other signals are removed. The interferogram data gives the relative water level change between two locations. Where there is measured water level data (within acceptable radius) the relative water level change can be converted into the absolute water level change. Jung et al. (2010) used interferometric SAR data from JERS-1 to study change in water levels for the Amazon and Congo rivers. The data were acquired for the low flow and high flow seasons and processed using the "two pass" method which includes flat earth phase removal and interferometric phase removal. Flooded vegetation, non-flooded areas and open water were differentiated based on backscatter "noise floor" and "mean interferometric coherence" of flooded and non-flooded areas. The temporal variation in water level $\mathrm{d}h/\mathrm{d}t$ was obtained by

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converting the phase changes in imagery to water level referenced to the WGS84 datum using altimeter measurements from Topex/Poseidon. Using dh/dt to characterize the Amazon floodplain showed increasing dh/dt from upstream to downstream within a complex pattern of interconnected channels with distinct boundaries and varying dh/dt. The Congo River characterization of dh/dt showed a uniformity and limited connectivity between the river and the adjoining wetlands. Schumann et al. (2007) used Envisat ASAR data to identify spatial clusters of channel roughness in order to calibrate a HEC-RAS model of Alzette river flooding. ERS SAR data of the same event and an aerial photo of an earlier event were used for validation of the calibrated model and overall model performance was compared to measured high water marks at seven points during the flood event. The mean cross sectional water levels used for model evaluation were estimated from the intersection of ASAR flood extent boundaries with LIDAR DEM. At each cross section, ranges of channel roughness values are run in a Monte Carlo simulation and the CDF's of the values are generated; these CDF's are compared with a CDF of uniformly distributed model (where model functioning is same over the entire parameter space). The deviation of the individual CDF's from the CDF of uniform distribution give the measure of the parameter sensitivity, the sum of which show the local functioning of the model at that cross section. CDF's with similar error characteristics are grouped into clusters using k-mean clustering. The results showed that two clusters of roughness values are enough.

Altimetry data from ENVISAT was combined with INSAR data from PALSAR and Radarsat-1 to compute absolute water level changes over the wetlands of Louisiana (Kim et al., 2009). Two pass INSAR method was used to check the two SAR images acquired at different times for phase differences. The ENVISAT altimetry data was used as the reference absolute water level change dh_0/dt to compute the all the changes in water level over the domain. The results obtained for water level changes showed better comparison with the wetland gauge than with the channel gauge which had many levees interrupting the flow. Westahoff et al. (2010) mapped probabilistic flood extents from SAR data by using the amount of backscatter and local incidence angles

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to create histograms that distinguish between wet and dry areas. The histograms were used to calculate the probability of flooding of every pixel.

2.2 Satellite altimetry data applications

Satellite altimetry (Fig. 2) works on the principle of return echo of pulses sent from the satellite nadir point and reflected from the surfaces of open water.

The height of the water surface is extracted from the distance between the satellite and the water body with reference to a local datum given as:

$$h = R - \left(c\frac{\Delta t}{2}\right) - \Sigma\mathrm{cor} \tag{1}$$

where h = water level, R = distance between the satellite altimeter and the water body, c = speed of light, $\Delta t/2$ = two way travel time of radar pulse, $\sum\mathrm{cor}$ = sum of for ionospheric, wet and dry tropospheric, and tidal corrections.

This principle (Fig. 2) has its limitations as the accuracy of the data is affected by atmospheric conditions, sensor and satellite characteristics, and reflectance conditions (Belaud et al., 2010).

Although satellite altimetry was developed and optimized to measure ocean level changes (not rivers), it has been demonstrated as a source of data over large rivers and lakes (Tarpanelli et al., 2013). Thus satellite altimetry data is used as the primary source of water level data in ungauged basins, and as a secondary data source to compare with measured data in sparsely gauged basins.

Often times the selection of altimeter water level data to be used depends on the time and season of acquisition (Papa et al., 2012). Data acquired during high flows give better measurements than low flow season data which usually have artefacts (in the form of islets, river banks, vegetation, etc.) that reduce the accuracy of the data in comparison with local gauge data. Analysing data over the Ganga-Brahmaputra Rivers, Papa et al. (2012) got mean errors less than cm when high flow altimetry data were compared

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with measured data, but low flow data showed errors larger tham 30 cm. Siddique-E-Akbor et al. (2011) used data from ENVISAT to compare with 1-D HECRAS model output water levels in order to check for accuracy and ability to get the seasonal trend. The model was run for periods of available ENVISAT data and the output compared with the ENVISAT time series. The results showed RMSE ranging from 0.70–2.4 m with the best correlation obtained during high flow seasons. The study suggest the use of calibrated hydrodynamic/hydrologic model outputs to benchmark altimetry data in ungauged and poorly gauged catchments.

Virtual altimeter gauging stations are located at the intersection of satellite tracts with water bodies. Santos da Silver et al. (2007) used virtual altimeter stations as water level data sources for ungauged catchments. They chose the median values of virtual stations that fell within river water bodies as water levels for the river and compared with measured values from gauging stations located within 20 km of the virtual stations using weighted linear regression. In order to avoid comparing two areas with different hydrological conditions, a ratio χ was computed of the discrepancy between the ENVISAT master points and the linear regression and the uncertainties associated to the ENVISAT master points. The developed method enabled a comparison that produced regression coefficient greater than 0.95 between the ENVISAT and gauges series. Santos da Silver et al. (2012) used 533 ENVISAT virtual stations and 106 gauging data to map extreme stage variations along 32 Amazon basin rivers and analysed for drought in the catchment. Using 2005 drought and 2009 flooding events as basis, data from 2002–2005 were analysed and time series of ENVISAT per virtual station were averaged to get monthly values. Values of the mean amplitude stage variation for the measured gauges showed good consistency with those of satellite altimetry and results for drought showed a range between −4 and 1 m of anomalies. Getirana et al. (2009) went even further and developed a rating curve of discharge values using virtual stations from ENVISAT for the upper part of the Branco River basin, Brazil. Virtual stations data were compared with nearby gauge data to check for seasonal similarity and trend, and those virtual stations with SDs < 0.1 m were chosen. The method

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used a distributed hydrological model to derive discharge values for the virtual stations. With model calibration and validation results showing good correlation with measured data, but the rating curve showed a 2.5–5 % increase in bias when compared with rating curves from measured data. The calibration results were affected by rainfall data spatial distribution.

Although use of satellite altimetry for river stage monitoring is usually applied to large rivers with few kilometre widths (Papa et al., 2012), altimetry data was used to estimate discharge in an ungauged part of the Po river basin (width: 200–300 m) using cross section data (Tarpanelli et al., 2013). They used a simplified routing model (RCM) based on upstream data, wave travel time and hydraulic conditions on two river sections to get the flow in the second river section. The results showed good agreement between simulated and insitu discharges, and gave lower RMSEs (relative to the mean observed discharge) than calculated results using an empirical equation also based on cross section geometry. Seyler et al. (2009) used altimetry virtual stations to estimate river slope. The calculated river slopes were used to get the river bank full discharge, and the results compared well with gauge data.

The use of altimeter data is limited by the long temporal resolution of satellite altimeters; which range from days to several weeks. Belaud et al. (2010) developed a method to interpolate river water levels in-between satellite observations in order to provide continuous data. The developed method used upstream ground station measurements and altimetry data as output to calibrate a propagation model by adjusting the satellite observed values. The propagation model used a transfer function to predict water level variations based on the relationship between the propagation times and water levels. The results were able to predict flood peaks during periods of no satellite coverage. Crétaux et al. (2011) addressed the problem of data gaps by combining three sets of altimetry data with MODIS measurements of water extent to monitor wetlands and floodplains in arid/semi arid regions. The MODIS data was used to classify the open water pixels whose relative values were then extracted from altimetry data.

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2.3 Optical satellite data

With the availability of more optical satellites with relatively low temporal resolutions globally, many scenes of archived data can be accessed and used for change detection studies and flood extent mapping in areas with little cloud cover. Penton and Overton (2007) combined flood mask extents from LandSat ETM of four flood events with LIDAR DEM to produce water heights for the floodplain. The heights of the flood mask water points were used to interpolate a water height surface which was subtracted from the DEM to produce the inundation map. Crétaux et al. (2011) used TOPEX/POSEIDON, ENVISAT1 and JASON2 data with MODIS measurements of water extent to monitor wetlands and floodplains in arid/semi arid regions. The results provided relative water heights, due to the low temporal resolution of the altimetry data sets.

Due to inaccessibility of the coastal terrain, many remote wetlands and swamps have few or no gauges, and are not covered by national gridding systems. As a result such areas are not included in topographic mapping projects; even where data is available the resolution is usually very coarse and not detailed (e.g. in Ezer and Liu, 2010). The morphology of coastal areas are affected by sediment supply, sea level change, littoral transport, storm surges, as well as hydrodynamics at the river mouths of deltaic areas (Kumar et al., 2010). Tidal flat morphology for example, changes with the tidal cycle and this can affect navigation, coastal defence, fishing, etc. The monitoring and modelling of tidal flat morphology is thus important (Mason et al., 2010). Apart from natural causes, coastal areas are also affected by human activities like sand mining, and construction of coastal infrastructure like ports, harbours, groins and other coastal defence systems.

Satellite data are used to study coastal morphological changes that affect the ecosystem and biodiversity of coastal areas. Kumar et al. (2010) studied the morphological changes in coastal parts Karnataka State, India using satellite and ancillary data. They calculated the rate of shoreline change over a ninety five year period (1910–2005) and used the results to predict future shoreline change rates to 2029. 25

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LandSat TM imageries were used to map the tidal mudflats of Cooks Inlet Alaska by integrating with an inundation model (Ezer and Liu, 2010). The morphology of Cooks Inlet is such that, tidal floods move much faster than the ebbing period which moves very slowly; therefore areas at the far end of the mudflats take several hours before tidal waters lower. To study their morphology as a test bed for prediction of floods and its effects, mapping of these frequently flooded areas was done using the Land-Sat imagery to delineate water only areas, and show the range of shoreline data and water levels. The model results calculated the water depth and gave the estimated 3-D topography of Cooks Inlet. Similarly, four LandSat TM imagery of the Ganges–Brahmaputra River mouth taken during low-flow and high-flow seasons were used by Islam et al. (2002) to estimate suspended sediment concentration. The method used converted the digital numbers of the imageries to radiance values and subsequently to spectral reflectance and linearly related them to suspended sediment concentration (SSC). The SSC results showed higher distribution of suspended sediments during high discharge seasons when the turbidity zone moves further seaward reaching debts of 10 m, than during low flow periods when the turbidity zone remains close to the shore. Yang and Ouchic (2012) used 2000–2009 optical and SAR satellite imagery and insitu data of the Han estuary in Korea to study bar morphology by relating it with tides and precipitation using regression analysis. The results showed areas closer to the sea correlating bar size/shape with tides, and areas closer to the river mouths correlating with precipitation.

Optical satellite images of Sumatra Island were used to study post tsunami coastal recovery based on beach nourishment and sediment refilling. Liew et al. (2010) used 1 m Ikonos images of pre-tsunami, tsunami, and post tsunami periods to show that coasts affected by tsunamis naturally rebuild to their former morphological states in areas with little anthropogenic activity. The results showed straight beaches rebuilding few weeks after the tsunami, but barrier beaches and lagoons recovery is much slower, enabling inland rivers and streams to directly discharge into the ocean. Thus, they

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concluded that due to the fast recovery of coastal features post tsunami, sedimentary deposits are better indicators of coastal geomorphology than tsunami events.

2.4 Satellite derived DEM data applications

Satellite data provide topographic information in the form of digital elevation models (DEM's) generated from radar echoes of spot heights (e.g. ASTER DEM, SRTM), and stereo pairs e.g. SPOT DEM. The most common and freely available DEM is the Shuttle Radar Topographic Mission (SRTM) DEM flown in February 2000 which covered 85 % of the earth's surface. SRTM is a C-band data which has an approximate vertical accuracy of 3.7 m, but reaches a range of 1.1–1.6 m on flatter floodplains (Syvitski et al., 2012).

At the land-water boundary in areas with gentle slopes, satellite DEMs can be used to measure river stage when combined with high resolution imagery. Such combinations have been used in flood inundation mapping, although there is less accuracy in situations where the water edge is obscured by vegetation (Smith, 1997). Syvitski et al. (2012) adjusted SRTM data using ocean heights measured by TOPEX/POSEIDON satellite altimeter to enable the mapping of floodplain zones. Advanced microwave Scanning Radiometer (AMSR-E) data provided brightness temperature measurements of the floodplain. Four floodplain zones were classified around the world from the 33 floodplains studied, namely: container valleys, floodplain depressions, nodal avulsions and delta plains. SRTM data measure surface level which over river channels is equivalent to water levels when the land water boundary in delineated. Jung et al. (2010) used insitu (bathymetry and cross sectional) data and SRTM DEM water levels to derive water surface slope, and calculate the discharge of the Brahmaputra River. The cross sectional water level was obtained by fitting a first degree polynomial function to the SRTM data elevation. The average calculated discharge results when compared to insitu gauge reading gave a difference of 2.3 %. Two DEM's of the Morecambe bay were used to determine the relative change in inter-tidal sediment volume above and below mean sea level (Mason et al., 2010). The first set of DEMs was derived from satellite SAR imagery and the second set from LiDAR. By using the sea height as zero level the LiDAR DEM was normalized to the same height as the SAR DEM. The relative change in sediment volume was derived by subtracting the normalized LiDAR DEM heights from the SAR DEM.

3 Limitations of satellite data application for surface water studies

As useful as satellite data applications have been in estimating surface water parameters, the measurements come with limitations due to sensor specifications/errors, pre and post data processing techniques, calibration, measurement conditions, satellite distance from the targets, etc. Optical satellite data for example is limited to day time acquisition due to its dependence on sunlight, and is not very useful in areas perpetually covered by clouds because the target cannot be reached (Smith, 1997).

3.1 SAR

The quality and usefulness of SAR data for hydrological studies depends on meteorological conditions (wind and rain), emergent vegetation, incidence angle and the polarisation mode used for data acquisition. Horizontal–Horizontal (HH) polarisation gives the best results for flood extent mapping than Vertical–Horizontal (VH) and Vertical–Vertical (VV) polarisations. However, VH and VV polarisations are also useful since VV polarisation data highlight vertical features like vegetation, and VH polarisation data reflect the horizontal nature of the smoothed flood water (Schumann et al., 2007). Another important factor for SAR data use in hydrology is the river size. Until the recent launch of TerraSAR-X, most available SAR satellites had large spatial resolutions which excluded smaller rivers from being captured; since it was difficult to delineate them in an image (Sun et al., 2009).

Use of Satellite SAR for flood extent mapping and model calibration can be improved through combination with other higher resolution data to increase precision in flood

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height determination. Satellite SAR used for delineation of water extent has the limitation of floodplain vegetation being included and classified as water pixels; more so the height of the SAR waterline does not show the variation in water height with flow direction. To improve the vertical accuracy of SAR waterline extent during floods, Mason et al. (2007) used waterline data extracted from ERS-1 SAR corrected with 1 m resolution LIDAR heights (along the Thames River bank) to calibrate a LISFLOOD model of flood extent. The output waterline when compared with waterline measured from aerial photos showed a lower root mean squared error than those obtained using SAR data only.

3.2 Altimetry

For river stage estimation and wetlands delineation, problems encountered with satellite altimetry data include: incorrect processing of radar echoes over rivers/lakes by satellite trackers, large temporal resolution, and lack of information within the data about the atmospheric wet vapour content over lakes/rivers (Crétaux et al., 2009). The errors recorded while using altimeter water level data can however be increased by incorrect choice of data; which frequently occurs when dry area data is retained within the data for computing water stages in low flow seasons (Santos da Silva et al., 2007). The difference between altimeter and gauge measurements also increases with distance between the points, topography and river width (León et al., 2006). When compared with gauge data, RMSEs of altimetry data measured over the Amazon have ranges from 30–70 cm using data from ENVISAT, ERS2, and GeoSaT (Tarpanelli et al., 2013), however at cross track situations where altimetry measurements are taken at the same location with a gauging station the difference can be < 20 cm (Seyler et al., 2009). The accuracy of altimeter measurements over rivers is also affected by the river width and the morphology of the river banks so that data on narrow rivers and vegetated banks have lower accuracy (Papa et al., 2012). Furthermore, the specifications of the altimetry system itself can affect quality of measurements; for example ENVISAT data have been shown to have lower RMSE compared to ERS2 data due to ENVISATs ability

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to switch frequency modes in response to change in terrain and its smaller bin width (Tarpanelli et al., 2013).

To improve the use of satellite altimetry data, interpolation methods have been developed to correct the data accuracy and precision by comparing the data with lakes and reservoir measurements. Thus the correlation with measured gauge data, range of RMSE and reduction in discrepancies have improved to levels > 0.95 correlation during validation (Ričko et al., 2012). Altimeter measurements over modified channels is however less reliable than that of natural catchments (Kim et al., 2009).

3.3 DEM

The limitation of satellite DEM is in the data quality. DEM data needed for modelling and other analyses that require topographic data depends on the acquisition method, the data processing and the characteristics of the mapped terrain. Satellite derived DEMs have less vertical accuracy, higher bias and higher RMSE than other DEMS derived from airborne LIDAR and airborne IFSAR (Fraser and Ravanbakhsh, 2011). However in spite of their limited accuracy, they are useful sources of topographic data especially for low lying coastal areas with gentle slopes (Gorokhovich and Voustianiouk, 2006) and therefore applicable for inundation modelling (Karlsson and Arnberg, 2011).

Generally, satellite based DEMs are those generated from radar echoes of spot heights (e.g. ASTER), but Mason et al. (2010) also derived DEMs from SAR images. The method involved using SAR water height to interpolate a set of waterlines, which were then used to produce a 50 m DEM of the intertidal zone with an accuracy of 40 cm. The method is however limited by the temporal de-correlation of the waterline heights.

4 Conclusions

Satellite remote sensing provides a source of hydrological data that is unhindered by geopolitical boundaries, has access to remote/unreachable areas, and provides fre-

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quent and reliable data (Jung et al., 2010). Available literature show that efforts have been made to develop an empirical relationship between satellite derived surface water extents (including flooded areas) with river stage or discharge. Results however show such relationships depend on the river system, thus inundation area can increase or decrease with stage. However for braided rivers, a power law correlation was established (Smith, 1997).

Use of satellite data to estimate hydrological parameters continues to increase due to greater availability of satellite data, improvement in knowledge of and utilization of satellite data, as well as expansion of research topics. A very important catalyst to this growth in satellite data utilization is the ability to use it in a Geographic Information System (GIS) environment. GIS enables comparison and deduction of relationships that exist amongst the complex data sources used for analysis. Thus relationships like the effects of land-use change on surrounding water bodies or water management are easily analysed and depicted. Consequently, satellite data is commonly used for: mapping of water bodies, testing of inundation models, soil moisture measurements, precipitation monitoring, estimation of evapo-transpiration, and mapping of flood extent.

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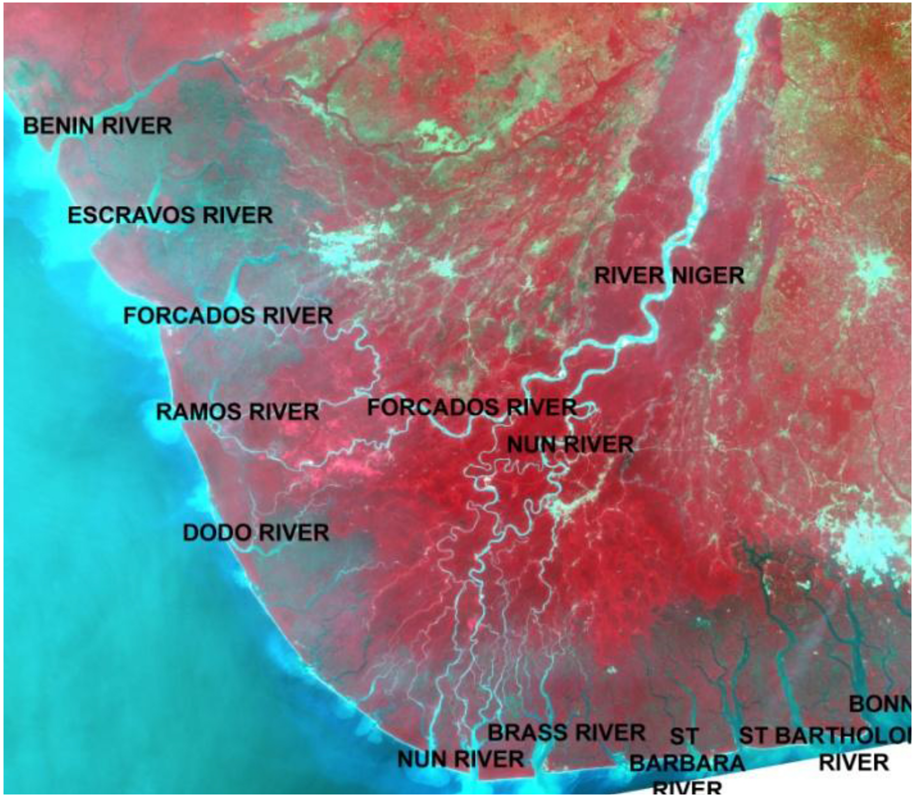

Figure 1. NigeriaSatX satellite image showing rivers in the Niger delta.

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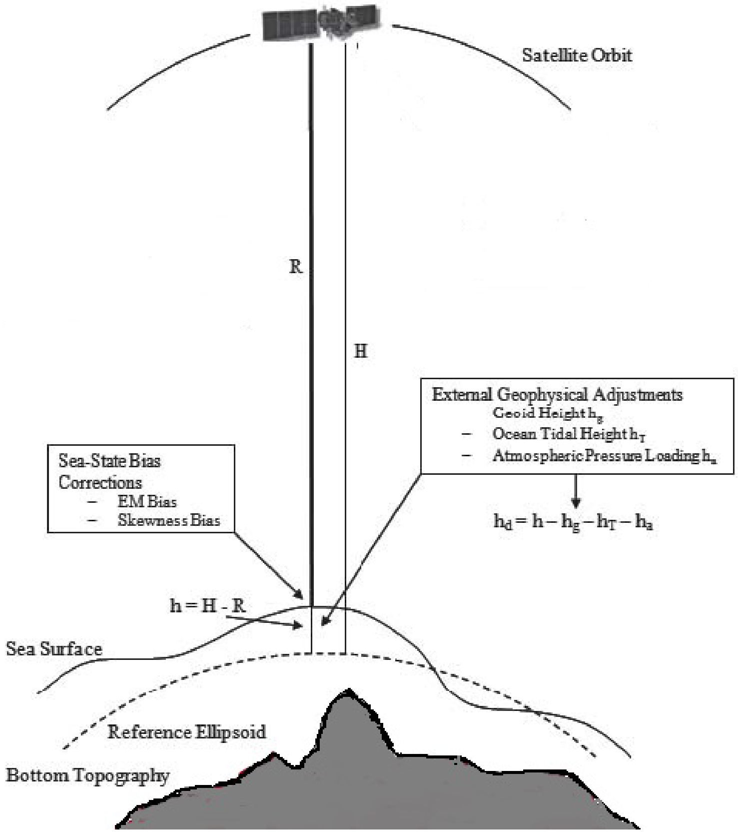

Figure 2. An illustration of height measurement using satellite Altimetry.