Suitability and Limitations of ENVISAT ASAR for Monitoring Small Reservoirs in a Semiarid Area

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Abstract—In semiarid regions, thousands of small reservoirs provide the rural population with water, but their storage volumes and hydrological impact are largely unknown. This paper analyzes the suitability of weather-independent radar satellite images for monitoring small reservoir surfaces. The surface areas of three reservoirs were extracted from 21 of 22 ENVISAT Advanced Synthetic Aperture Radar scenes, acquired bimonthly from June 2005 to August 2006. The reservoir surface areas were determined with a quasi-manual classification approach, as stringent classification rules often failed due to the spatial and temporal variability of the backscatter from the water. The land–water contrast is critical for the detection of water bodies. Additionally, wind has a significant impact on the classification results and affects the water surface and the backscattered radar signal (Bragg scattering) above a wind speed threshold of 2.6 m·s⁻¹. The analysis of 15 months of wind speed data shows that, on 96% of the days, wind speeds were below the Bragg scattering criterion at the time of night time acquisitions, as opposed to 50% during the morning acquisition time. Night time acquisitions are strongly advisable over day time acquisitions due to lower wind interference. Over the year, radar images are most affected by wind during the onset of the rainy season (May and June). We conclude that radar and optical systems are complimentary. Radar is suitable during the rainy season but is affected by wind and lack of vegetation context during the dry season.

Index Terms—Bragg scattering, radar, remote sensing, reservoirs, resource management, water, water resources, West Africa.

I. INTRODUCTION

IN MANY semiarid regions of the developing world, access to reliable water sources is the single most important factor for the agricultural economy. Thousands of small reservoirs dot the landscape, providing large volume water supply at the village level, improving food security, and stimulating economic development, particularly in rural areas.

Small reservoirs have been largely neglected in hydrological and water resource research because of the combination of several key characteristics: small size, existence in large numbers, and widespread distribution. These characteristics constitute their main advantages for the scattered rural population but make their monitoring difficult. Adequate ground-based data on small reservoir storage volumes are commonly not available, and conducting ground-based surveys and measurements is prohibitively expensive and time consuming on a regional scale. To overcome the lack of baseline data, Liebe et al. [1] classified the extent of small reservoir surface areas from Landsat ETM imagery and determined regional small reservoir storage volumes with a regional area–volume equation. Recently, further studies on regional area–volume relations of small reservoirs have been published, i.e., [2] and [3], indicating an interest in information on small reservoir storage volumes. Such regional storage volume estimates, however, depend on the ability to extract reservoir surface areas from satellite images. Optical satellite data yield good results in delineating small reservoir surface areas under cloud-free conditions, but the often cloudy conditions inhibit their use in an operational setting.

Although radar images, particularly in C-band such as ENVISAT’s Advanced Synthetic Aperture Radar (ASAR), have become routinely available, the classification of distributed inland water bodies has hardly been studied. Radar remote sensing is capable of penetrating clouds and is seen as a promising alternative to optical sensors. Successful application of radar in determining small reservoir extents would not only facilitate transferring this methodology to other areas for regional assessment of small reservoir storage but also allow regional monitoring of storage volumes.

This paper analyzes the suitability and limitations of radar remote sensing to determine small reservoir surface areas from a sequence of 22 ENVISAT ASAR images acquired bimonthly from June 2005 to August 2006. In contrast to the common analysis of single images, or image pairs, this larger image sequence ensures taking into account the seasonal variations, i.e., the changing vegetation context, and the large variability of backscatter from water surfaces, i.e., through wind-induced roughness. The surface areas are extracted from the image...
sequence for three reservoirs in the Upper East Region of Ghana and compared with in situ measurements based on bathymetric reservoir models and water level measurements.

II. RADAR REMOTE SENSING OF OPEN WATER

The detection of surface water on radar images is usually described as a simple task [4]. Smooth water surfaces act as specular reflectors and reflect most of the incoming radar signal away from the sensor. This is equivalent to very low radar backscatter signal returning to the sensor, which makes surface water bodies usually appear dark on radar images. This, however, is an oversimplification [5], as the surface roughness of water bodies is very variable, both spatially, within a water body, and temporally, leading to a wide range of backscatter. As will be shown here, this variability in backscatter can greatly affect the operational value of radar images for monitoring of small reservoirs. It is necessary to understand in some detail how contrast in backscatter between open water and surrounding land surface changes as a function of wind speed and direction, and vegetation density.

Wind-induced regularly spaced waves and ripples can lead to Bragg scattering [6], which results in elevated backscatter signals from the water surface. While wave crests oriented orthogonally to the look direction can produce Bragg scattering, wave crests oriented in line with the look direction may have no significant effect on the radar backscatter. The threshold wind speed value causing Bragg scattering in C-band is estimated to be at \( \sim 3 \text{ m} \cdot \text{s}^{-1} \) at 10 m above the surface [7]. This corresponds to a wind speed of 2.6 \( \text{m} \cdot \text{s}^{-1} \) at 2 m, using Sutton’s [8] equation for wind speed profiles.

Literature on open water delineation focuses on flood detection and presents various methods. Henderson [5] presented a study on the extraction of lakes from X-band radar in different environments, using manual interpretation to allow the inclusion of context and other interpretation clues in the analysis. Barber et al. [9] and Brakenrige et al. [10] visually interpret flood extents for the 1993 Assiniboine River flood in Manitoba, Canada, and the 1993 Mississippi River flood, respectively. Henry et al. [11] use band thresholds to classify inundated areas of the 2002 Elbe river flood. Likewise, Brivio et al. [12] map the extent of the flooded areas of the 1994 flood in the Regione Piemonte, Italy, based on visual interpretation and band thresholds. van de Giesen [13] mapped flooding in a West African floodplain during the dry and wet seasons with L- and C-band SIR images, distinguishing between open water and water with reeds. Nici et al. [14] compare flood detection from amplitude change detection to coherence methods from multipass SAR data. Horrit et al. [15] use a statistical active contour model to delineate flood boundaries, and Heremans et al. [16] compare flood delineation results from and active contour model to that of an object-oriented classification technique. Context is an important factor for the delineation of water bodies. The degree of accuracy that small water bodies can be extracted from the radar images largely depends on the land–water contrast. For a distinct land–water contrast, a low and coherent backscatter from the water body is desirable that stands in distinct contrast to its surroundings, ideally producing higher signal returns.

Due to the high dielectric constant of water, the penetration depth of the radar signal into the water and, hence, volume scattering and depolarization is low [4]. Reflections off of the water surface are thus predominantly like-polarized. The return from the water bodies in the HV band is therefore expected to be low. Tall reeds growing on the sides of the reservoirs during the rainy season can act as corner reflectors, which lead to high backscatter signals in radar images due to double bounces which can also partially depolarize the radar signal [4]. In the radar image, this accentuates the land–water boundary and facilitates its detection [5]. In the HH band, water bodies can also be classified well when the water surface acts as a specular reflector, i.e., ideally under calm conditions. The vast portion of the radar burst is then scattered away from the sensor, leaving the water body to appear dark in the image. Under windy conditions, however, a rough water surface reflects more of the incoming radar signal back to the sensor. These elevated returns under windy conditions, particularly in the like-polarized bands, are again due to the high dielectric constant of water. As wind speeds are not always uniform over the entire water body, elevated backscatter can occur in patches or affect larger parts of the reservoir. Although elevated backscatter from the water surface is detrimental to its classification in most cases, it can also be seen as a signal typical for water bodies, which can be helpful in classifying reservoirs.

Images acquired in dual-polarization mode can therefore provide further clues for the land–water separation. In general, like-polarized images have a better overall image contrast [4], but VV is affected much more by Bragg scattering relative to the HH and HV response [17].

In this paper, the different subtleties of open water delineation with ENVISAT ASAR will be explored, leading to a comprehensive overview of the strengths and drawbacks.

III. STUDY REGION

The study is conducted in a 23-km² watershed surrounding the village of Tanga Natinga in the Upper East Region of Ghana, West Africa (Fig. 1). Three small reservoirs, referred to as Reservoirs 1, 2, and 3, supply the population of the villages of Tanga, Weega, and Toende with water for irrigation and gardening, livestock watering, household use, building, and fishing [18], [19]. Maximum depths are 5.2 m for Reservoir 1, 4.7 m for Reservoir 2, and 4.3 m for Reservoir 3. Climatically, the research area is located in the semiarid tropics and is characterized by a monomodal rainy season from July to September, with 986 mm of average annual rainfall and 2050 mm of average annual potential evaporation [20]. The area lies in the northern Guinea savanna zone, and the vegetation is characterized by open woodland, interspersed with annual grasses [21]. Due to high population pressure, large areas are under agricultural use. Between reservoirs and agricultural land, there is usually a grass buffer of 10–30 m. The vegetation dynamics in the vicinity of the reservoirs are largely driven by the rainfall patterns. After the first rains, grasses grow around the reservoirs. During the rainy season, the grasses can grow up to 2 m tall, and extensive reeds are found in the tail parts of the reservoirs. In the dry season, the grasses are often harvested.
for roofing material, etc., burned, or they deteriorate, leaving behind bare dry soil with sparse knee-high grass tussocks as vegetation. The direct vicinity of the reservoirs is then free of vegetation, exposing the bare banks of the reservoirs.

IV. DATA SETS AND METHODS

A. Reservoir Bathymetry and Areas

Bathymetric reservoir models and water level measurements serve as ground reference data for comparison with reservoir surface areas determined with ENVISAT images. The bathymetric models were generated from GPS tagged water depth measurements and reservoir outlines as described by Liebe et al. [1]. Water level measurements are used together with the bathymetric models to determine the surface area and storage volumes of the reservoirs.

Water levels were measured with pressure transducers at 15-min intervals. These were used to determine ground reference data of reservoir surface areas at the time of image acquisition, which are compared with the radar-based results. For Reservoirs 1 and 2, water level data are available from June 6, 2005 to February 21, 2006 and for Reservoir 3 from June 6, 2005 to August 3, 2006.

B. Wind Speed and Wind Direction Data

Wind-induced waves and ripples may influence the radar signal return from water surfaces. Besides wind speed, the wind direction is of importance, as it determines the crest orientation of the wind-induced waves. Assuming that wind produces waves with crests orthogonal to the wind direction, high wind speeds with wind directions orthogonally to the look direction may affect the backscatter from the water bodies less than wind directions in line with the look direction. Wind speed was measured on the center of Reservoir 3 and is available from October 2005 onward. In addition, wind speed and wind direction were measured at three locations on the shore of Reservoir 3 (Fig. 1) at 2-min intervals, starting in August 2005.

C. ENVISAT Satellite Data

In this paper, 22 ENVISAT ASAR acquisitions are used with a roughly bimonthly coverage from June 2005 to August 2006. ENVISAT ASAR is a C-band radar. We used APG images, with a nominal spatial resolution of 30 m and a pixel spacing of 12.5 m. ENVISAT’s ASAR instrument can acquire images in dual-polarization mode and produce HH- and VV-, HH- and HV-, or VV- and VH-polarized image pairs [22]. In this paper, we have chosen dual-polarized acquisitions with the band combinations HH and HV. This combination has also been found useful in flood delineation by Henry et al. [11]. The scenes were acquired from different swaths (IS1–IS6) with incidence angles ranging from an overall minimum of 12.5° to a maximum of 43.77° throughout the scenes. The look direction is 81.45° on ascending and 261.45° on descending images. Images were acquired in both ascending (night time acquisition) and descending (morning acquisition) nodes to take into account the diurnal wind patterns, which determine the occurrence of Bragg scattering.

D. Classification of Small Reservoir Surface Areas

Several approaches were tested to determine the surface areas of the reservoirs, such as the active contour method or snake
combinations with the best visual land–water contrast were chosen for the classification. The reservoirs were classified on either the HV or HH band alone, or an image generated by multiplying the bands \(-1 \times (\text{HV} \times \text{HH})\), prior to classification.

V. RESULTS

A. Reservoir Classification

While some of the images clearly showed the reservoirs on both the HV and HH bands [e.g., Fig. 3(a) and (b)], their visibility was often drastically better in one of the bands [e.g., Fig. 3(e) and (f)]. Given the large variability in radar backscatter from water surfaces, obtaining classification results from a large number of image acquisitions requires a relaxed classification scheme like the quasi-manual approach used here. The three following cases outline the importance of land–water contrast, its variations, and the effect of incoherent backscatter from a water body.

An example of excellent contrast between land and water for both bands is the scene acquired on September 2, 2005. The water bodies appear dark in the images, have sharp borders, and can be classified from the low radar backscatter range of the HV and HH bands [Fig. 3(a) and (b)]. At the time of image acquisition, weather station 1 recorded no wind, whereas stations 2 and 3 recorded wind speeds of 1.3 and 3.0 m \( \cdot \) s\(^{-1}\), respectively. The wind direction produced wave crests expected to be in line with the look direction [Fig. 3(a) and (c)], which is adverse to Bragg scattering, and therefore, the water surface does not produce elevated backscatter. In the scatter plot in Fig. 3(d), “water pixels” aggregate in a cluster with low HV and HH backscatter. Part of the reason why the reservoirs in this image are so obvious is that, during this part of the year, the reservoirs are filled to their full extent and are flanked by tall vegetation. To delineate the water bodies, the active contour method [Fig. 4(a)], classification on the HH–HV scatter plot [Fig. 4(b)], and growing of a training area [Fig. 4(c)] all worked similarly well. Comparably excellent land–water contrast was only found in the image acquired on October 7, 2005, and less distinct, but still well on July 11, 2005, July 29, 2005, November 28, 2005, July 11, 2006, August 3, 2006, and August 15, 2006.

An example of an image that only shows the reservoirs well in one band was acquired on September 19, 2005. The land–water contrast is distinct in the HV band [Fig. 3(e)], but in the HH band [Fig. 3(f)], the major portions of the water surface of Reservoirs 2 and 3 show elevated backscatter. While the vegetation surrounding the reservoirs is still as tall as on September 2, 2005, the reservoir outlines cannot be readily determined from the HH band [Fig. 3(f) and (g)]. The elevated backscatter is likely to be caused by wind-induced ripples. At the time the image was acquired, wind speeds of 1.3 m \( \cdot \) s\(^{-1}\) and gusts up to 1.86 m \( \cdot \) s\(^{-1}\) were measured at weather station 1. The wind direction recorded at weather station 1 produces wave crests expected to be roughly orthogonal to the look direction [Fig. 3(e) and (g)], a favorable constellation for Bragg scattering. While the water surface in the HV band does not seem to be affected, the surfaces of Reservoirs 2 and 3 [zoomed reservoir in Fig. 3(g)] are made up of two distinct patches: a dark strip on the windward side, where the wind may not have formed ripples...
Fig. 3. ENVISAT ASAR bands and scatter plots. Left [(a)–(d)]: Acquisition from September 2, 2005. The reservoirs are distinct in both (a) the HV band and (b) the HH band. The zoom on Reservoir 3 in (c) band HH shows good land water contrast. Wind speeds, wind directions (arrows), and expected crest orientation of wind-induced waves are depicted for (black) weather station 1, (blue) weather station 2, and (white) weather station 3. Wave crests are roughly in line with the look direction and, thus, adverse for Bragg scattering. The (d) HV–HH scatterplot shows a water cluster in the lower backscatter ranges. The colors indicate the frequency of backscatter ranges, with frequency increasing from blue to green, yellow, and red. Right [(e)–(h)]: Acquisition from September 19, 2005. The reservoirs are distinct in (e) the HV band, but in (f) the HH band, reservoirs 2 and 3 are not distinctly visible. The zoom on Reservoir 3 in (g) band HH shows extensive areas of the water surface affected by Bragg scattering. Wave crests are at an angle to the look direction, which is more likely to produce Bragg scattering. The (h) HV–HH scatterplot shows a water cluster in the lower backscatter ranges and a second cluster with low backscatter in HV and elevated backscatter in HH due to Bragg scattering.
yet, and elevated backscatter from the major part of the surface area toward the leeward side. In the scatter plot in Fig. 3(h), there are two distinctive clusters corresponding to open water: one cluster with low backscatter in both bands (red outlines), similar to Fig. 3(d), and a cluster with low backscatter in the HV band, but elevated backscatter in band HH [green outlines in Fig. 3(g); scatter plot in Fig. 3(h)] due to Bragg scattering. The active contour method [Fig. 4(d)] and growing of a training area method [Fig. 4(f)] still work well on the HV band, while the reservoir area obtained through combining the two clusters that delineate in the HV–HH scatter plot [Fig. 3(h)] is too small [Fig. 4(e)]. Good land–water contrast in the HV band and patches of both low backscatter and elevated Bragg scattering in the HH band are present in the acquisitions from August 15, 2005, September 19, 2005, and October 24, 2005. On the images acquired on January 27, 2006, February 21, 2006, March 3, 2006, and June 13, 2006, the land–water contrast was good in the HH band and poorer in the HV band. This emphasizes the need for a flexible methodology for categorizing the parts of the radar images that correspond to reservoirs, i.e., one rigid method will incorrectly categorize the reservoir pixels on many of the images.

Fig. 5 shows an image acquisition of the same area from April 20, 2006, in which both bands fail to distinctly distinguish the water bodies from their surroundings. This image acquisition falls into the dry season when the reservoir levels and surface areas have decreased significantly and the water bodies are surrounded by previously water-covered smooth banks, which have a surface roughness similar to the water surface. The tall vegetation, which surrounded the reservoirs in the rainy season, is now essentially absent. Additionally, high wind speeds and wind directions favorable for generating wave crests orthogonally to the look direction (Fig. 5), and thus Bragg scattering, are recorded. The loss of land–water contrast in the dryer and less vegetated environment is reflected in the HV–HH scatter plot with the signal from water bodies scattered throughout (Fig. 5). Although we were unable to delineate the reservoirs in the images from April 20, 2006, we were able to do so for all the other days of radar image acquisition, even several images with similar contrast issues, e.g., images from June 6, 2005, June 24, 2005, November 11, 2005, December 16, 2005, May 9, 2006, and June 29, 2006.

In analogy to van de Giesen’s [13] flood plain analysis, image histogram characteristics were used for a qualitative image rating (Table I). The band histograms were calculated for the zoom window on Reservoir 3, for the extent as shown in Fig. 3(c). In cases of pronounced land–water contrast in a band, the histogram shows a double peak [Fig. 6(a)], where the peak in the lower backscatter range is due to the water body, and the peak at higher backscatter range is due to the vegetation. In bands with low or no land–water contrast, the histogram produces only a single peak [Fig. 6(b)], where the water and land pixels produced backscatter at similar intensities. Acquisitions with double peaks in both bands [i.e., Fig. 6(b)] were rated as “excellent”
Fig. 5. (a)–(d) ENVISAT ASAR acquisition from April 20, 2006. In neither (a) the HV band nor (b) the HH band, the reservoirs are distinctly visible. The zoom on Reservoir 3 in (c) band HH shows poor land water contrast. Wind speeds, wind directions (arrows; no record for weather station 2), and expected crest orientation of wind-induced waves are favorable for Bragg scattering. The (d) HV–HH scatterplot shows no distinct water cluster that is different from the backscatter from the land.

(x), whereas those acquisitions with a double peak in one band and a single peak in the other band were rated as “good” (g). Acquisitions with single peaks in both band histograms [i.e., Fig. 6(b)] were rated as “poor” (p) for land–water separation.

The quasi-manual classification method has been arrived at through trial and error. The tested snake algorithm and band threshold approach gave very poor results on images with less than excellent land–water contrast, often not providing any sensible delineation. For this reason, no quantitative comparison of the different methods is provided.

B. Comparison of Radar- and Bathymetry-Based Reservoir Sizes

Reservoir surface areas could be extracted from 21 of the 22 ENVISAT scenes used in this paper. These are compared with surface areas determined from the reservoirs’ bathymetrical models, and water levels at the time of image acquisition. The overall performance of the reservoir size extraction compared well to bathymetry-based reservoir sizes ($r^2 = 0.92$, Fig. 7). The classification performance, however, varied for the individual reservoirs. The reservoir area classification of Reservoir 1 ($r^2 = 0.83$) is mainly affected by the extensive reeds found in the tail part of the reservoir. These are not identified as part of the water body, whereas they are included in the bathymetric model, causing a discrepancy. Reservoir 2 was the most difficult to classify. Its southern shore is composed of a very smooth bare sandy loam, which diminishes the land–water contrast. Nevertheless, the highest coefficient of correlation was achieved for Reservoir 2 ($r^2 = 0.95$). Reservoir 3 was often affected by wind, which leads to patches of elevated backscatter.

C. Wind Speeds and Scene Acquisition Times

The influence of wind speed at the time of image acquisition on the land–water contrast is apparent from the average wind speeds. Table I presents ENVISAT acquisition characteristics, and averaged wind speed and direction records. The acquisitions grouped in the aforementioned example of acquisitions with excellent land–water contrast (“x,” Table I) are associated with wind speeds of 0.6, 1.3, 1.4, 1.5, 1.6, and 3.9 m · s$^{-1}$, whereas images with good contrast but with some Bragg scattering effects (“g,” Table I) show wind speeds of 0.2, 0.4, 0.7, 1.4, 1.6, 1.9, and 3.1 m · s$^{-1}$. With two exceptions (February 21, 2006 and July 11, 2006), these acquisitions are associated with low wind speeds. The acquisitions listed in the third example with poor contrast between land and water (“p,” Table I) coincide with high wind speeds of 3.2, 3.2, 3.6, 3.7, and 4.6 m · s$^{-1}$.

Wind speeds were generally higher during the morning than during the evening (Fig. 8). During the morning acquisition time, on 214 out of 430 days, the 2-m wind speed exceeds the 2.6-m · s$^{-1}$ Bragg scattering threshold, i.e., on only 50% of the days, wind speeds were below the threshold. For evening overpasses, the Bragg scattering criterion is surpassed only during 18 out of 430 days, i.e., on 97% of the days, wind speeds were below the threshold.
VI. DISCUSSION

The surface extent of small reservoirs could be extracted from 21 of the 22 ENVISAT ASAR scenes used in this paper, using the best band or band combination. The combination of both bands generally improved the classification result. For acquisition dates with image pairs consisting of an image with good and one with poor land–water contrast or Bragg scattering effects, the classification was performed on a single band. Based on ESA’s recommendation, image-mode VV-polarized images should be used to map open water [24]. Experience with a large number of ERS VV images shows that, for the purpose of monitoring small reservoirs, this is not the optimal choice. Instead, dual-polarized images are preferable for operational purposes. In general, HH images give the best results, but the HV images form a backup in case Bragg scattering occurs.

Stringent classification rules that allow simple and automated surface area extraction only produce results on a small number of images with excellent land–water contrast and coherent backscatter from within the water body. Due to the great variability and incoherence in the backscatter from water bodies, and in land–water contrast, stringent rules, however, fail quickly. With more flexible classification rules, such as the quasi-manual approach used here, good results were produced on all but one image. The fact that we have to manually identify the training area is comparable to purely visual techniques commonly employed in radar image analysis [5], [9], [10] and should not necessarily be considered a problem. Our quasi-manual approach differs from a fully manual, or visual, approach in that it is still based on backscatter statistics of the training areas and relationships among neighboring pixels, which allows us to set criteria that categorize “water pixels” somewhat less subjectively, particularly when Bragg scattering makes it difficult to visually identify all boundary pixels.

A comparison between reservoir sizes extracted from the ENVISAT ASAR scenes and the bathymetry-based outlines (Fig. 9) shows that the ENVISAT results (point markers) are generally lower than the bathymetry-based surface areas (line graphs). Fig. 9 also shows that, as the reservoirs attain their maximum fill level, this difference increases and eventually produces an almost constant offset during the period when the reservoirs are full. As the reservoir levels fall, the difference quickly diminishes. This increasing area differential with increasing fill levels, and the eventual offset at the maximum fill levels, is due to the development of wetland vegetation in the inflow part of the small reservoirs. When the fill levels approach the maximum capacity, distinct land–water boundaries diminish, and the open water body often gradually changes into an extensive wetland at its inflow part. At these higher

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TABLE I

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* Land-water contrast rating based on categories described in 5.3. x = excellent, g = good, p = poor, n = none

When the reservoir levels become lower again, this effect quickly diminishes together with the presence of wetlands, and the radar- and bathymetry-based area estimates converge. By taking into account this overestimation of the bathymetric data at full reservoir capacity as compared with ENVISAT classified reservoir areas, the overall classification results are acceptable.

The land–water separability is influenced by the vegetation context, and the natural variability of the water surface, often as a response to wind speed, which affects parts of or the entire reservoir. To a large degree, the presence of tall vegetation around the reservoirs drastically improves the delineation of water bodies, as the low backscatter from the water surface itself stands in distinct contrast to the high backscatter from its edges, due to the high potential for double bounces off of the water and the vertical vegetation. Such double bounces however only occur during the rainy season and, shortly thereafter, when the water levels are high and the vegetation is still lush. At the same time, exact delineation of the reservoirs can become difficult in the tail part at full capacity, when there is no clear distinction between open water and wetland. During the dry season, when the water levels have decreased, the water bodies are mainly surrounded by the smoothly transgressing basin sides, which are mostly free of vegetation. Under these conditions, the land–water contrast is less distinct.

Wind was identified to affect the backscatter from water bodies. Images with very poor land–water contrast, and the acquisition from which the reservoirs could not be classified, coincided with high wind speeds and wind directions which are propitious for Bragg scattering, whereas most images with excellent land–water contrast were acquired at low wind speeds and/or wind directions which are unfavorable for Bragg scattering. Choosing night time acquisitions clearly gives a higher chance of acquisitions at lower wind speeds. As is typical for most semiarid areas, the onset of the rainy season, here from May to June, is a period with relatively high wind speeds. During this period, the chance to acquire scenes with clearly distinguishable small reservoirs diminishes.

A threshold value of $2.6 \text{ m} \cdot \text{s}^{-1}$ at 2 m has been put forward as criterion for the occurrence of Bragg scatter. In the case of small reservoirs, we do indeed see that when winds are above this threshold, Bragg scatter occurs if the wave crests are perpendicular to the look direction. It should be noted that there were also occasions where minor wind gusts at low wind speed ($1.0 \text{ m} \cdot \text{s}^{-1}$) in the look direction caused Bragg scatter. In such cases, the use of the dual-polarization mode ENVISAT images is essential, because cross-polarized images are less affected.

VII. CONCLUSION

The use of radar remote sensing as a tool for water resource monitoring is promising due to its ability to penetrate clouds, but the delineation of water bodies is difficult to automate. For time series analysis, an automated extraction of water bodies would be desirable but is not always possible due to the large variation in the radar backscatter from the water surface and to the changing ambient conditions. The quasi-manual method
Fig. 8. Measured wind speeds over the course of the year for morning and evening overpasses. (Dark blue) Night time acquisitions yield a much higher chance to obtain images where the water bodies are not affected by wind-induced waves. Over a period of 15 months, wind speeds recorded during the (dark blue) night time acquisitions were below the Bragg criterion on 96% of the days, whereas during the (magenta) morning acquisitions, wind speeds were below the Bragg criterion on only 50% of the observed days. The ten-day averages (morning acquisition on red; night acquisition in light blue) show that wind speeds during the morning acquisitions are generally higher than those recorded at night and also show a seasonal cycle. During the dryer months from December to July, wind speeds are particularly high during the morning acquisitions.

Fig. 9. Comparison of (markers) reservoir sizes from ENVISAT classification with (lines) reservoir sizes from bathymetrical models. Note the almost constant offset between bathymetry- and satellite-based surface areas at the maximum fill levels, which is due to the inclusion of wetlands in the bathymetric model. These differences diminish with decreasing reservoir size, when the wetlands fall dry.

The analysis of the radar image time series indicates that the land–water contrast, which is of greatest importance for the detection of water bodies, varies significantly with the seasons. Radar images acquired during the rainy season showed the best land–water contrast and were most easily classified. In the dry season, with smaller water bodies and lack of surrounding vegetation, their classification was more difficult as the land–water contrast diminishes. Toward, and throughout the dry season, the water detection on radar imagery is most difficult, as the land–water contrast suffers from the lack of vegetation context. Under such conditions, optical systems yield good results [1], even on small water bodies, and independent of the surrounding vegetation and wind conditions, as long as cloud-free images can be obtained. This leads to the important conclusion that optical- and radar-based methods can be seen as seasonally complementary for surface water detection, particularly in semiarid areas.

The backscatter signal of water bodies is significantly influenced by wind-induced waves and wave crest orientation. The analysis shows that Bragg scattering effects emerge at much lower wind speeds than ESA's wind speed threshold for Bragg scattering, which translates to wind speeds of 2.6 m·s⁻¹ (at 2 m height); however, the heavily affected acquisitions with poor land water contrast are all associated with wind speeds well above this threshold. The analysis of wind speed prevalence at the time of the morning and night time image acquisitions shows a distinct difference. Night time acquisitions are much less likely affected by wind than the morning acquisitions. For the delineation of water bodies, selecting night time acquisitions yields a significantly higher chance of
obtaining radar images at wind speed conditions below the Bragg criterion. Although Bragg scattering was also observed below the 2.6 m·s⁻¹ threshold, Bragg producing gusts are less likely during the night time acquisitions, when the atmosphere commonly has stabilized.

Overall, this paper shows that regional to basin scale inventories of small inland water bodies are readily possible with ENVISAT ASAR images. In combination with regional area–volume equations (i.e., [1]–[3]), basin-wide small reservoir storage volumes can be estimated, and the impact of further development can be assessed and monitored. With the ever improving digital elevation models, it is foreseeable that area–volume equations can be determined adequately from these data, which will allow for regional and basin-wide small reservoir storage volume estimates at any given location. Further research could clarify whether ALOS PALSAR’s L-band data yield better land–water separation under the various wind conditions and seasonal changes in vegetation context, which would allow extracting small reservoirs and other inland water bodies at a higher degree of automation.

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