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EXTRACTION OF SMALL DAM RESERVOIRS USING A COMBINATION OF DIGITAL TERRAIN MODEL AND WATER MASK DERIVED FROM SATELLITE IMAGES

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Dam reservoirs account for only a small fraction of the global freshwater but they have major importance for human activities, providing water for agriculture, domestic, recreational, and industrial use, especially in a context of water scarcity induced by climate change[1]. They also have major impacts on the hydro- and ecosystems[2]. While they are subject to numerous studies across multiple disciplinary fields [3, 4], no exhaustive database of existing dam reservoirs is available, and the available data are limited to the largest reservoirs. Thus, there is a need for a method to automatically extract dam reservoirs from widely available data such as satellite images. This task is different from the broader water surface extraction task [5, 6] as the goal is also to distinguish dam reservoirs from other waterbodies. Some approaches have been proposed to achieve it, for example by Van Soesbergen et al. [7]. However, this extraction task using only single images can be very difficult for very small waterbodies (below 1 hectare).

To improve the results, we propose a new method that combines a water mask and a digital elevation model (DEM). The water mask can be extracted from any very high-resolution satellite image: optical or SAR. The DEM can be derived from SAR interferometric data (TanDEM-X) or optical stereo images (future CO3D mission[8]).

The idea behind our method is the fact that dams are built to prevent water from flowing in the direction of the downward terrain slope, as illustrated in Figure 1 (right). Where there is a dam, the terrain's upward slope (right red arrow) is oriented in the same direction as the inward-pointing normal vector to the waterbody contour (right blue arrow). Contrariwise, where there is no dam, the upward slope is always oriented in the opposite direction as the inward normal vector to the contour (i.e. the banks are higher than the water), which prevents the water from flowing out of the waterbody. The dot product between the inward-pointing normal vector to the water contour and the gradient of the elevation (DEM) is positive where there is a dam and negative where there is no dam. We use the gradient of the smoothed water mask (i.e. the binary mask convoluted with a Gaussian kernel) as a surrogate for the inward-pointing normal vector and the gradient of the smoothed DEM as a surrogate for the upward slope direction. We call the dot product between these two

gradients the Gradients Dot Product (GDP). It can be computed in every pixel using the method presented below and is positive in dams and negative elsewhere. This is illustrated in Figure 3 where the values of the pixels of these images are plotted along a line A-B that contains a dam (as in Figure 2). It can be noted that the GDP is computed using the gradient of the DEM in the neighborhood of the waterbody, but not in the waterbody itself. Identifying a waterbody corresponding to a dam reservoir using its GDP image is a straightforward task as the dam area is positive while the non-dam contours of the waterbody are negative (see examples in Figure 5). This task can be done using a CNN classifier. With adequate training, such a classifier is relatively robust to errors in the GDP caused by errors in the DEM and the binary water mask. This also allows for distinguishing usual dam reservoirs from other artificial reservoirs that are completely surrounded by a levee (e.g. reservoirs called *bassines* in French).

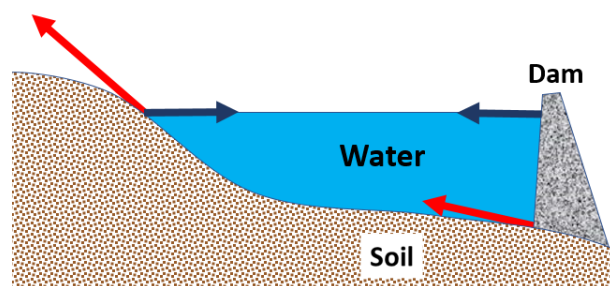


Fig. 1. Sectional view of a reservoir showing a dam contour (right) and a non-dam contour (left). Where the dam is located, the upward slope direction (red arrows) is in the same direction as the inward direction for the water mask (blue arrows). Here the proposed GDP image is therefore positive. At the non-dam water bank (right) they are in opposite directions and the GDP is negative.

The proposed method consists of 5 steps, as presented in Figure 2:

1. The binary water mask is computed using a water extraction method. In our tests, we used a Random Forest approach based on radiometric indices followed by a

morphological regularization.

2. The water mask is cropped around the considered waterbody.
3. The DEM is cropped according to the same footprint
4. Both cropped images are processed and combined to obtain a Gradient Dot Product (GDP) image of the same size. The two components of each gradient are computed using a convolution of the Sobel kernels with the water mask image smoothed beforehand by convolution with a Gaussian kernel. The gradient dot product image can then be computed by summing the pixel-wise multiplications of the gradients components x and y images. A post-processing is applied to set the pixels inside the initial water mask to zero, as the DEM is not known inside the waterbody.
5. This GDP image is given to a CNN classifier which classifies between dam reservoir and other waterbodies. We chose a ResNet [9] network that has been pre-trained using the ImageNet dataset. As labeled data are scarce, we give the RGB color representation of the GDP image (blue to red color scale) as input to the classifier after normalization, rotation, and re-sampling steps. This RGB representation is closer to the natural images of ImageNet, which limits the amount of training required.

We tested our method using Pléiades optical images (70cm resolution 50cm pixels) and the RGE Altitude DEM. The training and validation dataset used to train the classifier consists in manually-labelled data from the Haute-Garonne department in France. It contains 817 samples: 409 for the "dam reservoir" class and 408 for other water bodies. The test dataset contains 134 dam reservoirs and 65 other water bodies from the Tarn department. We compared our method to a classification method using another ResNet-based CNN classifier that we trained and tested using the binary water mask and the DEM as distinct inputs. We compared the accuracy obtained with the train dataset for three area ranges: between 0.1 and 0.2 hectare, between 0.2 and 0.7 hectare, and greater than 0.7 hectare. We obtained an accuracy of 0.58, 0.75, and 0.89 respectively while for the separated mask/DEM classifier it was 0.54, 0.60, and 0.73. This shows a significant improvement for the GDP-based method compared to the separate binary mask and DEM.

The experiments show that our approach based on the Gradients Dot Product (GDP) yields encouraging results. Future work should consider applying the method to other sources of binary mask and DEM as well as other geographic areas. This method could also be adapted to extract other kinds of waterbodies, for example, "bassines" agricultural reservoirs. The proposed Gradient Dot Product could also be used as an input to detect the accurate location of the

dam within a given reservoir, for example, for the Stockwater method [10]

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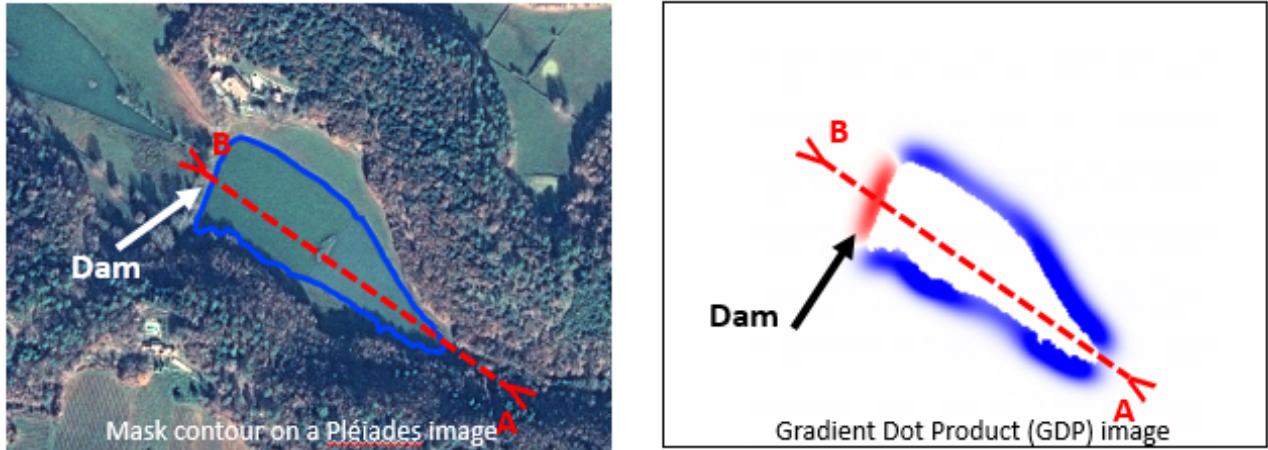


Fig. 2. Example of a dam reservoir. The contour of the water mask is displayed on a the corresponding Pléiades optical image (left). A dam can be seen in the image. The dashed line AB corresponds to the section along which the values of the pixels are plotted in Figure 3 and to the section of the cross-sectional view Figure 1 (from left to right). The right Figure shows the corresponding GDP image, with the negative values in blue and the positive values in red.

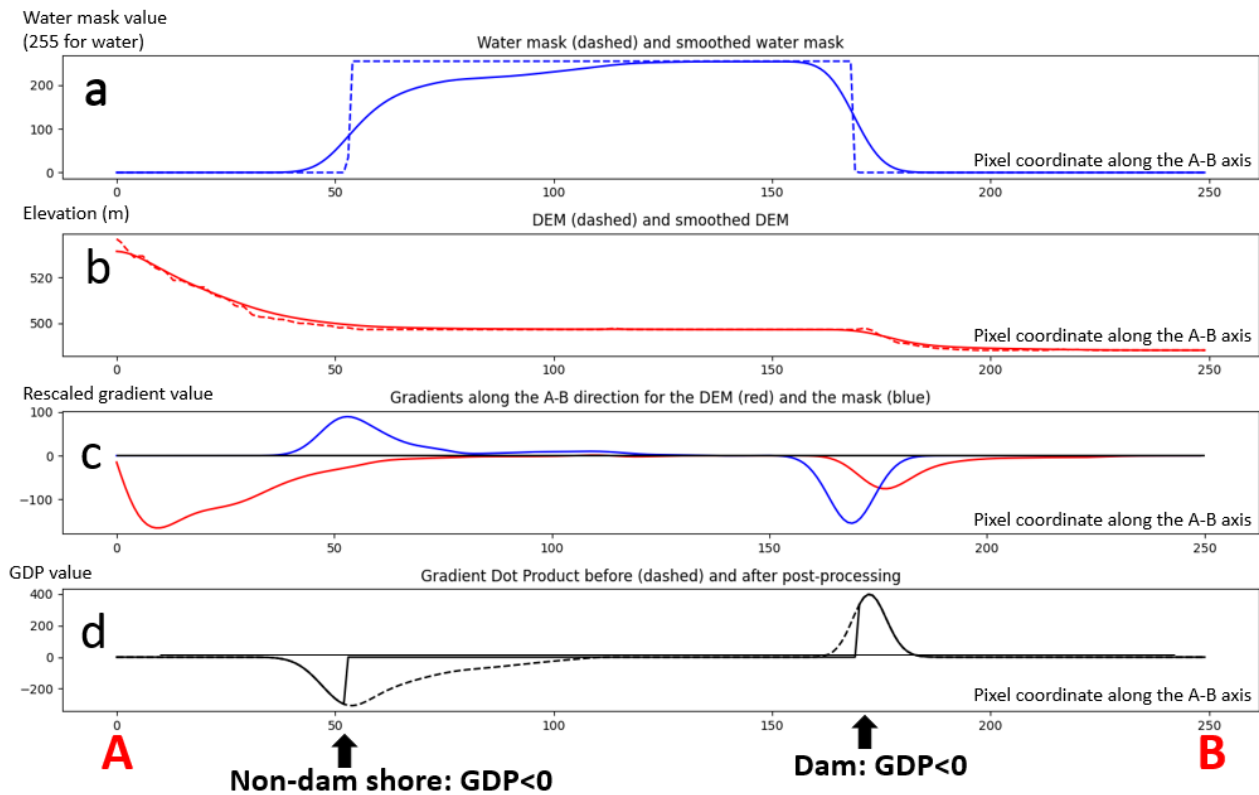


Fig. 3. Pixel values of the images along the A-B line defined Figure 3, for the corresponding mask and DEM. (a) for the mask raster (dashed line) and smoothed mask values (plain line). (b) DEM elevation (dashed red line) and smoothed DEM elevation (plain red line) (c) gradients values (projected on the A-B axis) of the smoothed mask (red) and of the smoothed DEM (red). (d) shows the GDP before (dotted line) and after (plain line) the post-processing. As two-dimensional kernels are used for smoothing and derivation, the values for one profile cannot be inferred from the other one-dimensional profiles.

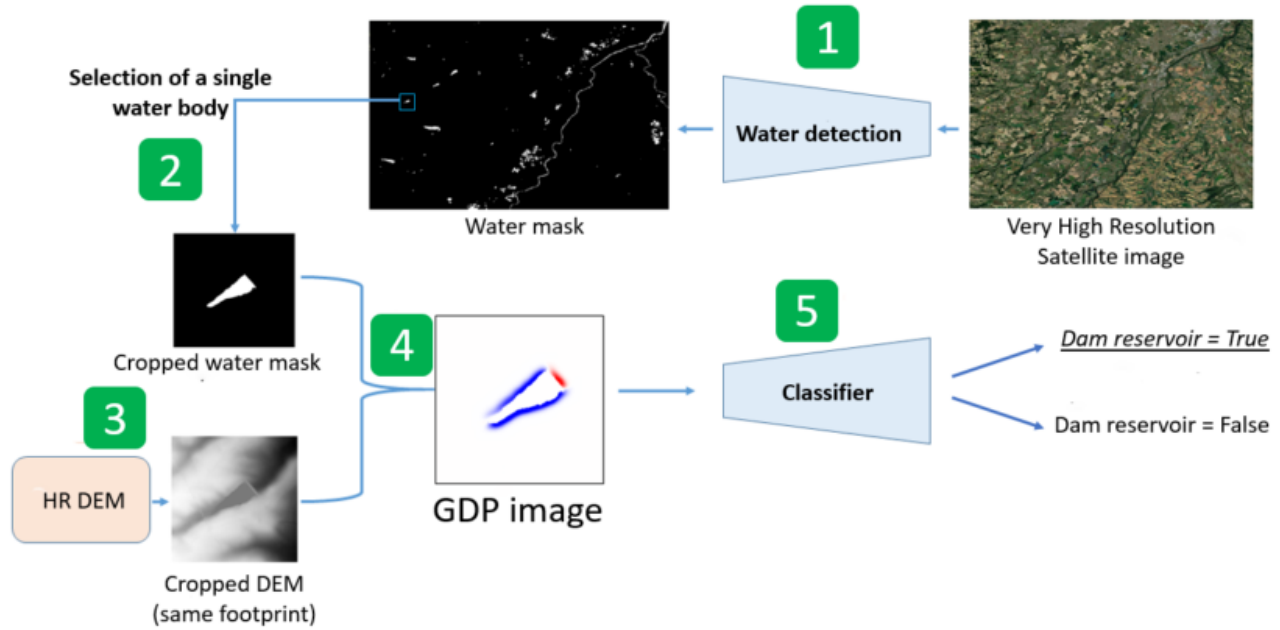


Fig. 4. General principle of the propose method. The numbers correspond to the steps presented below. In the GDP (Gradient Dot Product) image, the negative values are displayed in blue, and the positive values (that correspond to the location of the dam) are in red.

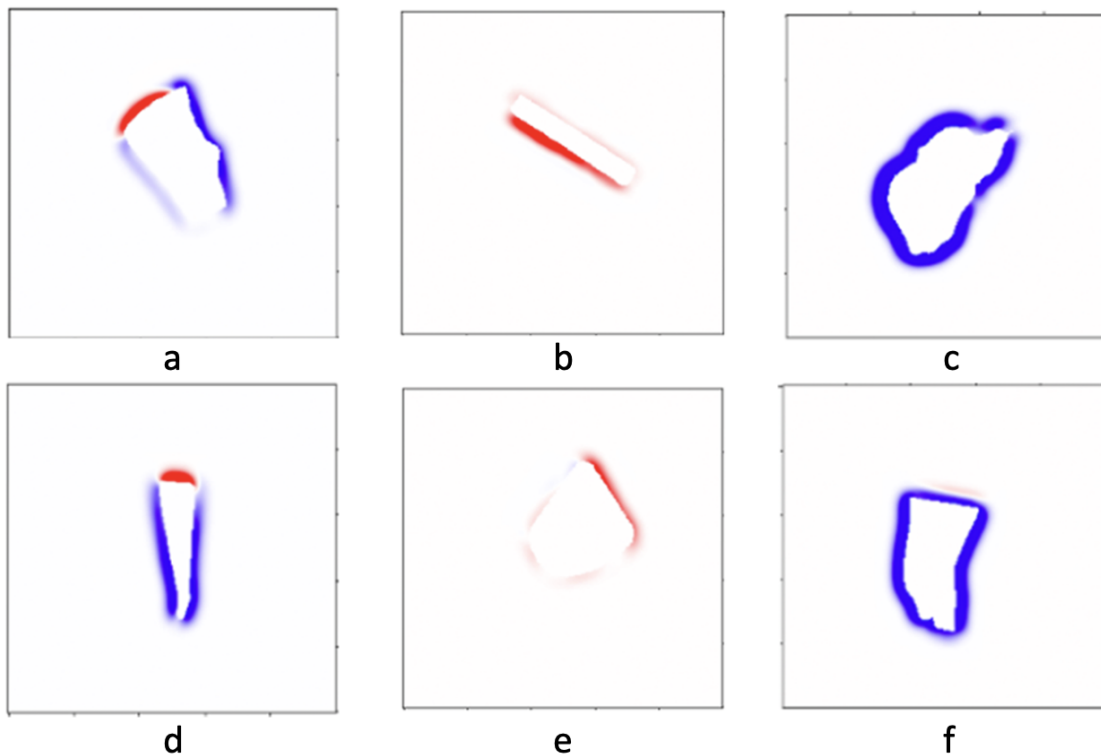


Fig. 5. Examples of GDP images for different waterbodies : typical dam reservoir (a,d), typical non-dam waterbodies (b,e), and raised basins (c,f). The negative values are displayed in blue, and the positive values (that correspond to the location of the dam) are in red.