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An automatic water body area monitoring algorithm for satellite images based on Markov Random Fields

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Our knowledge about spatial and temporal variation of hydrological parameters are surprisingly poor, because most of it is based on in situ stations and the number of stations have reduced dramatically during the past decades. On the other hand, remote sensing techniques have proven their ability to measure different parameters of Earth phenomena. Optical and SAR satellite imagery provide the opportunity to monitor the spatial change in coastline, which can serve as a way to determine the water extent repeatedly in an appropriate time interval.

An appropriate classification technique to separate water and land is the backbone of each automatic water body monitoring. Due to changes in the water level, river and lake extent, atmosphere, sunlight radiation and onboard calibration of the satellite over time, most of the pixel-based classification techniques fail to determine accurate water masks. Beyond pixel intensity, spatial correlation between neighboring pixels is another source of information that should be used to decide the label of pixels. Water bodies have strong spatial correlation in satellite images. Therefore including contextual information as additional constraint into the procedure of water body monitoring improves the accuracy of the derived water masks significantly.

In this study, we present an automatic algorithm for water body area monitoring based on maximum a posteriori (MAP) estimation of Markov Random Fields (MRF). First we collect all available images from selected case studies during the monitoring period. Then for each image separately we apply a k-means clustering to derive a primary water mask. After that we develop a MRF using pixel values and the primary water mask for each image. Then among the different realizations of the field we select the one that maximizes the posterior estimation. We solve this optimization problem using graph cut techniques. A graph with two terminals is constructed, after which the best labelling structure for the image is defined by finding the maximum-flow (minimum-cut) solution using the Dinic algorithm. At the end, we calculate the water body area using the final water mask.