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## Estimation of suspended sediment concentrations in the Rhine River using Landsat Satellite Images

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# Estimation of suspended sediment concentrations in the Rhine River using Landsat Satellite Images

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**Abstract.** The traditional methods for measuring water quality and suspended sediment concentrations (SSC) are time-consuming and often do not give the spatial and temporal detail needed for assessment of the water quality and sediment transport. The determination of the suspended sediment concentrations using remote sensing through the main channel and tributaries of Rhine River can provide valuable information to assess the spatial and temporal of the suspended sediment. The main objective of this study is to estimate the suspended sediment concentrations (SSC) using Landsat satellite images. This study developed a method of quantifying SSC based on Landsat imagery and corresponding SSC data from the International Commission for the Protection of the Rhine (IKSR) and Dutch Rijkswaterstaat from 1995 to 2016. The model was built using the ratio of logarithmic transformation of a red/green band and logarithmic transformation of SSC based on *in-situ* sampling measurements. The SSC model works well and shows satisfactory performance. Landsat satellites (Thematic Mapper (TM), Multi-Spectral Scanner (MSS), Enhanced Thematic Mapper (ETM), Operational Land Imager (OLI)) explained an acceptable result accuracy.

## 1. Introduction

Suspended sediment consists of organic and inorganic materials carried within the water column [1]. Suspended sediment is a natural and crucial component and plays a crucial role in the hydrological, ecological and geomorphological functioning of the river system [2]. A correct estimation of suspended sediment can be a useful indicator for assessing the effect of land use changes and engineering practices in watercourses [3].

Time series of suspended sediment concentrations were analysed for several main Rhine River sections and its tributary rivers for the period between 1995 and 2016. These *in-situ* measurements have a long record data availability. However, although such measurements are accurate and often detailed in time, they do not give a detailed spatial view of SSC needed for assessment of the water quality [4]. The prediction of the suspended sediment using remote sensing through the main channel and tributaries of Rhine River can provide valuable information to assess the spatial and temporal patterns of the suspended sediment.

Since recently, the remote sensing method can be used as an alternative method to predict the suspended sediment. The evidential relationship between the suspended sediments and radiance or reflectance in a



specific spectral wave band or the combination of wave bands have been demonstrated [4]. Furthermore, several studies have found that blue, green, red, NIR bands of Landsat and the use of single band [5] and band ratio [6] is well correlated with suspended sediments. Landsat sensors: Thematic Mapper (TM), Multi-Spectral Scanner (MSS), Enhanced Thematic Mapper (ETM), and Operational used fairly successfully to measure most of the crucial water quality parameters, such as suspended sediment [7].

The objective of this study is to estimate the suspended sediment concentrations (SSC) using Landsat satellite images. The SSC model was built in several steps: first, data from SSC *in-situ* measurements were compiled from 1995-2016. Second, the reflectance values from Landsat satellite images were extracted to create the empirical model for predicting the SSC. Third, Landsat satellite images were correlated with SSC *in-situ* measurements which coincide on the same day. Once the model was built, the model performance was evaluated using multiple metrics.

## 2. Methods

### 2.1. Study Area

The Rhine River is the second largest river in Europe and has a total catchment area of 165,000 km<sup>2</sup>. The river originates from European Alps with the total length of the river 1320 km to the North Sea and its annual discharge near the mouth is 2500 m<sup>3</sup>/s. The largest discharge is at the Lower Rhine with a maximum discharge approximately 12,000 m<sup>3</sup>/s and the minimum discharge with only 267 m<sup>3</sup>/s at the Upper Rhine. In the summer, water mostly comes from snowmelt in the southern part of the drainage basin. In the winter, the central part of the Rhine River gives a substantial water contribution to downstream.

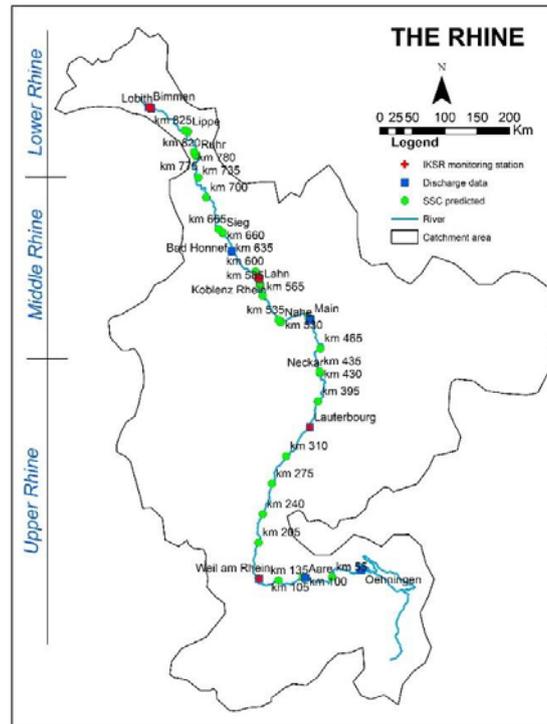
### 2.2. SSC Measurements

#### *Suspended Sediment Concentration (SSC)*

Bi-weekly SSCs are available at several main Rhine River monitoring stations: Weil am Rhein, Lauterbourg, Koblenz Rhein, and Bimmen, which have been registered by the International Commission for the Protection of the Rhine (IKSR). For the Lobith monitoring station, daily SSC was provided by the Dutch Rijkswaterstaat from 1995 to 2016. Fig.2.1 shows the locations of these stations. The SSC from measurements were used to create and evaluate the SSC model using spectral data from satellite imagery.

#### *Landsat Imagery*

The Landsat satellite was chosen for this study for its wide range of spatial and temporal data available for Rhine River, and it has an acceptable spatial resolution 30-meter x 30-meter for mapping large rivers. Data from four Landsat satellites were used in this study: both Landsat 4 and Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 8 (OLI). Each satellite crosses every point on Earth once every 16 days with 8 days offset data acquisition, while two Landsat satellites were in operation. The Landsat data used covered the time period from 1995 to 2016.



**Figure 1.** Locations of *in-situ* SSC observation data, discharge data, and SSC model output

### 2.3. Land-Water Masking

Water levels and depths in the Rhine River vary in space and over time. A water mask was applied to reduce the influence of upwelling. Therefore, sampling locations were filtered which only SSC of at more than 60 m from the bank of the water body was applied in the analysis. To detect channel morphological changes from 1995-2016, the shoreline was observed from Joint Research Center (JRC) Monthly Water History v1.0 image collection (JRC/GSW1\_0/MonthlyHistory) which contains maps of the location and temporal distribution of surface water [8].

The EROS Science Processing Architecture (ESPA) on-demand interface corrects atmospheric effects of all landsat satellite images using the most mature approach Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS). LEDAPS accounts for scene spectral variations caused by atmospheric effects including ozone concentration, column water vapor, elevation and surface pressure, and aerosol optical thickness. Through LEDAPS, data were calibrated, converted to top-of-atmosphere reflectance, and atmospherically corrected using 6S methodology. By removing the atmospheric effects, this allows the all scene to be treated based on application standard models [9].

The CFmask algorithm allows us to filter poor quality observations of each Landsat imagery [10]. The CF mask algorithm identifies each pixel as clear sky or each pixel identified as clouds, cloud shadows, snow or water for each Landsat image [11]. In this study, CFmask pixel QA band acts to mask the cloud and cloud shadow in the Landsat images. Only 100% cloud-free of each Landsat scene was used in model development to avoid the effects of cloud cover as clouds represent highly unreliable values. Moreover, we used CFmask QA band to define pixels as water and was used for gap-filled Landsat scenes that are out of JRC data availability (JRC/GSW1\_0/MonthlyHistory).

### 2.4. Model Development

The method for SSC prediction was carried out in the following steps. First, data from SSC *in-situ* measurements were compiled from 1995-2016. Second, the reflectance value of bands and band ratio from Landsat satellite images was extracted to create an empirical model for predicting the SSC. Third, the reflectance value of bands and band ratio from Landsat satellite images were correlated with SSC *in-situ* measurements which coincide on the same day producing matrix correlation. The highest correlations were attempted further to build the linear regression.

The average relation between the reflectance value of bands or band ratio and SSC *in-situ* measurements was the form of exponential relationship (equation 1). The ordinary least squares regression method was used to make a regression of *a* and *b* coefficient. However, the underestimates come when the suspended sediment concentration was predicted using band or band ratio. Therefore, the bias correction (*CF*) was then used to correct underestimation (equation 2). The estimated  $SSC_{correct}$  (equation 3) then is calculated by multiplying  $10^a$  and SSC (equation 1) by *CF* (equation 2).

$$SSC = a X^b \tag{equation 1}$$

$$CF = \exp(2,651 * S^2) \tag{equation 2}$$

$$SSC_{correct} = 10^a * SSC * CF \tag{equation 3}$$

Where  $S^2$  is the mean square error of the log-transformed regression (in log-10 units) and X is band or band ratio. The results were evaluated by calculating the error bias, Root Mean Square Error (RMSE), coefficient of determination ( $R^2$ ), and Nash-Sutcliffe Efficiency (NSE).

## 3. Result and Discussion

### 3.1. SSC prediction

All possible bands and band ratios that have the highest correlation coefficient of 0.53 are  $\frac{red:green}{2}$ ,  $\frac{red}{blue}$ , and  $\frac{red}{green}$  (Table 3.1). Several studies have suggested to use  $\frac{red}{green}$  band ratio to model SSC in surface waters [6,12,13]. Therefore, the  $\frac{red}{green}$  ratio was chosen in this study to build the empirical model.

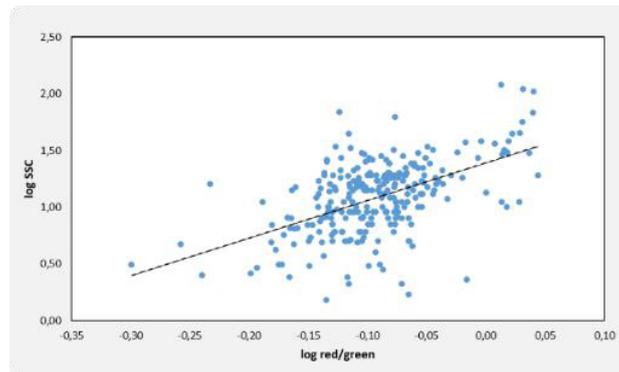
**Table 1.** Correlation matrix for the log spectral values of each band/ band ratios and log SSC

	SSC	blue	green	NIR	red	$\frac{blue}{green}$	$\frac{blue}{red}$	$\frac{blue}{NIR}$	$\frac{green}{red}$	$\frac{green}{NIR}$	$\frac{red}{NIR}$	$\frac{NIR}{green}$	$\frac{green+red}{2}$	$\frac{red:green}{2}$	$\frac{red}{blue}$	$\frac{red}{green}$
SSC	1.00															
blue	0.22	1.00														
green	0.39	0.88	1.00													
NIR	0.22	0.68	0.62	1.00												
red	0.49	0.84	0.96	0.61	1.00											
$\frac{blue}{green}$	-0.29	0.42	-0.06	0.25	-0.07	1.00										
$\frac{blue}{red}$	-0.53	0.05	-0.36	-0.04	-0.50	0.79	1.00									
$\frac{red}{blue}$	-0.12	-0.09	-0.10	-0.79	-0.13	0.01	0.09	1.00								
$\frac{NIR}{green}$	-0.53	-0.44	-0.51	-0.38	-0.74	0.06	0.65	0.15	1.00							
$\frac{red}{green}$	0.00	-0.24	-0.07	-0.83	-0.10	-0.37	-0.21	0.93	0.11	1.00						
$\frac{NIR}{red}$	0.16	-0.11	0.08	-0.71	0.12	-0.38	-0.40	0.87	-0.19	0.96	1.00					
$\frac{NIR}{green}$	0.00	0.24	0.07	0.83	0.10	0.37	0.21	-0.93	-0.11	-1.00	-0.96	1.00				
$\frac{green+red}{2}$	0.43	0.87	0.99	0.62	0.98	-0.05	-0.41	-0.11	-0.60	-0.08	0.10	0.08	1.00			
$\frac{red:green}{2}$	0.53	0.44	0.51	0.38	0.74	-0.06	-0.65	-0.15	-1.00	-0.11	0.19	0.11	0.60	1.00		
$\frac{red}{blue}$	0.53	-0.05	0.36	0.04	0.50	-0.79	-1.00	-0.09	-0.65	0.21	0.40	-0.21	0.41	0.65	1.00	
$\frac{red}{green}$	0.53	0.44	0.51	0.38	0.74	-0.06	-0.65	-0.15	-1.00	-0.11	0.19	0.11	0.60	1.00	0.65	1.00

The regression results in the following equation to estimate the suspended sediment:

$$SSC = 30.03X^{3.3187}$$

where  $X = \frac{red}{green}$  ratio, the equation then was used to create the model (Fig. 3.1) and to evaluate the model. The bias correction is already used to correct underestimation. However, the linear fit produces a low coefficient correlation which is 0.3. The standard error is 0.28 mg/L which is considered as an acceptable value [14]. Table. 3.2 shows the error statistics of empirical model.



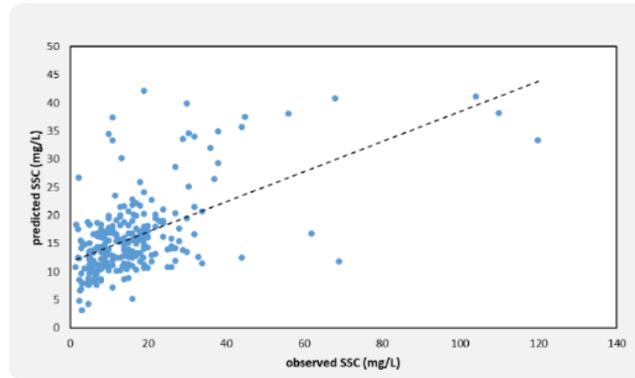
**Figure 2.** Model calibration using the red/green band ratio with linear fit from equation 1

**Table 2.** Error statistics of empirical model

$R^2$	intercept	gradient	st. error (mg/L)
0.30	1.39	3.32	0.28

### 3.2. Model Evaluation

The SSC model ranges widely from 1.5 mg/L to 120 mg/L (Fig. 3.2). The model results in a higher  $R^2$ , RMSE, and NSE values for 0.43, 11.08 mg/L, and 0.38 respectively in the wet season than in dry season 0.30, 12.66 mg/L, and 0.29 (Table 3.2). Meanwhile, the model produced in the dry season obtains higher error/ bias than in the wet season, which are 1.01 mg/L and -2.60 mg/L respectively. Error statistics for all validation dataset and wet season produce a coefficient of determination ( $R^2$ ) lower than 0.5, which is considered unacceptable. However, error statistics model such as Nash-Sutcliffe model efficiency coefficient (NSE) and Root Mean Square Error (RMSE) of the entire datasets and season variations are well within an acceptable model range based on (Moriassi et al., 2007). The bias of the model is -0.02 mg/L for the entire datasets, indicating that the model performs well in estimating SSC for the overall average. Fig 3.3 shows map of suspended sediment concentration in the Rhine River derived from Landsat satellite images.

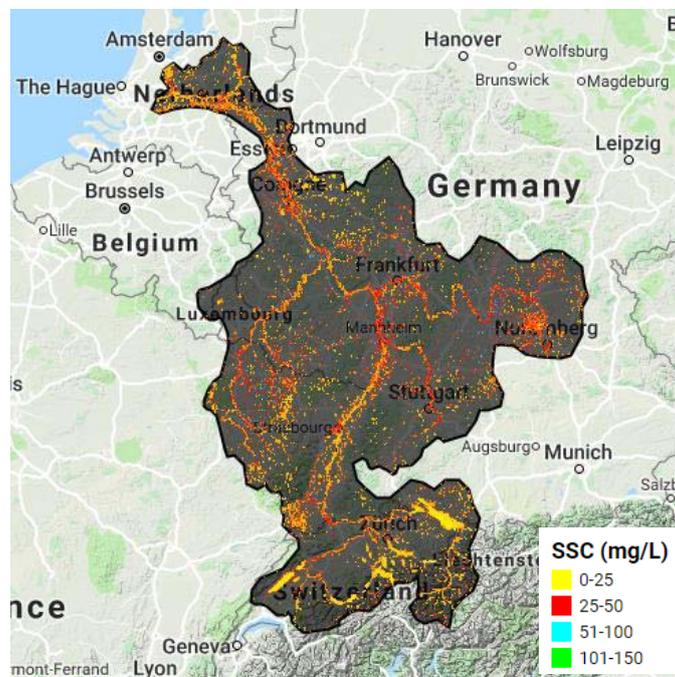


**Figure 3.** Model evaluation (validation) of observed SSC compared to predicted SSC

**Table 3.** Error statistics for model evaluation of observed SSC compared to predicted SSC

	$R^2$	error/bias (mg/L)	RMSE (mg/L)	NSE (-)
wet season	0.43	-2.60	11.08	0.38
dry season	0.30	1.01	12.66	0.29
all dataset	0.32	-0.02	12.23	0.33

**Figure 4.** Map of suspended sediment concentration in the Rhine River derived from Landsat satellite images



### 3.3. Suitability and Uncertainties of Remote Sensing for the Assessment Suspended Sediment

There are several limitations of SSC model that must be considered for analyzing the result. However, Landsat appears to be the most suitable for predicting the SSC in Rhine River since it provides 30 m spatial resolution and offers a long-term temporal record (30 years). Although another satellite image such as MODIS produces daily data, small spatial resolution of 250 appears to be not suitable to discriminate SSC particle in the Rhine River [5].

The model is built using remote sensing which has limitations in temporal resolution. Temporal resolution represents the information of date acquisition of satellite and the cloud cover. Each satellite crosses every point on Earth once every 16 days with 8 days offset data acquisition, while two Landsat satellites were in operation. However, the discharge data and SSC used for the regression model are bi-weekly. Therefore, this condition results in only limited satellite images, discharge, and SSC data that correspond each other. Moreover, cloud cover results in worse satellite images quality in the wet season, resulting in the higher error model in the wet season than in the dry season and only limited number of satellite images are used to build the SSC model. As a result, estimated SSC has a smaller range than SSC observed. Since only limited range is used, the extreme conditions are probably missing.

The model effectively predicts suspended sediment for values less than 20 mg/L and is estimated with less precision above those values (Fig. 3.2). Values are under-estimated constantly at high concentration (>20 mg/L). Of the SSC value, 84% were below than 20 mg/L and 16% were above 20 mg/L. The model which works well at low concentration levels tended to saturate predicted values to a constant value at higher concentrations [15-16]. Model saturation for high SSC value was probably as a result of a small fraction of high SSC data, large variation of the largest and the lowest SSC value and processing limitation [17]. Another reason, the higher reflectance values suggest that dissolved organic matter and the chlorophyll can adjust dramatically within a green and red wavelength [16]. In contrast, this study shows no discernible pattern in which the spectral band was used among model that saturate. We suggest instead that a large variation of maximum and minimum SSC values may result in saturation at high SSC. The model could only be analyzed for its SSC in 1-2 meter from the water columns and would adjust the result in the shallow water [6,18].

### 3.4. Long-Term Monitoring and Applications

Landsat provides relatively high spatial and temporal resolution. Despite, the temporal resolution is not sufficient for daily or weekly observation of SSC in the river, since the data are frequently collected every 14 days and with 8 days offset data acquisition, while two Landsat satellites were in operation.

To build a long-term SSC analysis, other satellite instruments that have better spatial and temporal resolution are required. Furthermore, the SSC model result derived from satellite images could be delivered extensively to users on an operational basis such as web-application. Users then could define a period time of interest, region interest, and seasonal interest. Users could also download the results with the variation of format type such as a graphic/chart or in a table.

#### 4. Conclusion

This study demonstrates the use of SSC can be predicted based on Landsat satellite images to map the spatial variation of SSC in the Rhine River. We found that the SSC predictions based on the  $\frac{red}{green}$  ratio yields satisfactory results. This is especially true for SSC less than 20 mg/L, but the predictions above this concentration is less precise. The Landsat images demonstrated to be very useful for the routine monitoring of SSC in rivers and to have a strong potential as a source of information for managers or stakeholders in the assessment and sustainable use of surface water resources.

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