A MULTI-MODAL SYSTEM FOR MONITORING OF WATER QUALITY – SETUP AND FIRST RESULTS FROM PASSAUNA RESERVOIR

Jens Kern and Andreas Schenk

Karlsruhe Institute of Technology, Institute of Photogrammetry and Remote Sensing,
Englerstr. 7, 76131 Karlsruhe, Germany
{jens.kern, andreas.schenk}@kit.edu

ABSTRACT

An ensured supply of drinking water is a major purpose of water reservoirs. The input and accumulation of sediments and nutrients in the reservoir body can cause strong growth of algae and cyanobacteria which leads to significant quality-related use restrictions. Continuous monitoring of the reservoir water quality can help to indicate such trends at an early stage. Small and lightweight cameras are promising to be used on UAV platforms as close range remote sensing system. We present the set up of such a UAV monitoring system which main elements are a hyperspectral camera and a thermal infrared imaging sensor and show first results from two field campaigns at the Passaúna reservoir close to Curitiba, Brazil.

Key words – *Water Quality, UAV, Hyperspectral, Thermal, Close Range Imaging*

1. INTRODUCTION

In many parts of the world, reservoirs are indispensable for the production of drinking water and electricity. More than 59 000 reservoirs produce 20 % of the global electricity and supply up to 40 % of the irrigation area. Around 12 % of the reservoirs with large scale dams are used for water supply including drinking water [1–3]. Their operation, however, is associated with a far-reaching encroachment in the continuum of river courses and they form a sink, especially for particulate material and substances bound to it. One immediately noticeable consequence of this is the eutrophication of the reservoirs. The strong growth of algae and cyanobacteria then leads to significant quality-related use restrictions, especially in the production of drinking water.

Such conditions require long-term, integrated management strategies that adequately take into account the water and material flows in catchment areas as well as the essential reactions in water reservoirs. A minimum monitoring concept which consists of pointwise and continuous in-situ measurements as well as spatially extended and recurrent remote sensing observations is one of the aims of the German-Brazilian research project "Multidisciplinary data acquisition as the key for a globally applicable water resource management (MuDak-WRM)" to provide an adequate monitoring of the water quality in the Passaúna reservoir in the federal state Paraná, Brazil.

In the MuDak-WRM project a close range remote sensing system is developed to support the qualitative and quantitative measurement of material input to water supply reservoirs. It is envisaged to address the scale leaps between satellite remote sensing with reservoir wide coverage on the one hand and localized, distributed in-situ measurements on the other hand. The latter enables the exact determination of all relevant parameters, but only at single observation points and in a time-consuming and cost-intensive manner. Multi- and hyperspectral remote sensing in contrast enable an automatic and spatially extensive analysis of water quality parameters, but limited to optically active parameters in the near surface water column, prone to gaps in data provision as consequence of cloud coverage and usually with less accurate parameter estimates. In comparison to other methods, satellite images suffer from low spectral resolution and the atmospheric correction is inevitable [4].

In this project we employ a close range remote sensing system, which is composed of a hyperspectral camera and a thermal infrared imaging sensor on a UAV to observe the material input at the inflow of the reservoir and dissemination in the reservoir. The close range remote sensing approach is chosen as it bridges the inherent scale jump between ground-based in-situ measurements and well established and sufficiently tested satellite-borne multispectral remote sensing approaches for water quality observation on the data as well as on the model side. By means of hyperspectral imaging sensors which are installed on a UAV platform, the traditional remote sensing approach is transferred to ground-level platforms in order to develop a flexible, cost-effective and cloud independent method of water remote sensing. When mounted on a UAV system, the new generation of low cost and lightweight hyperspectral sensors offer a flexible acquisition of data with high resolution in space and time. However, these mostly uncooled instruments have less radiometric and geometric precision and reduced fidelity compared to sensors that are installed on satellite platforms. In this paper we present the system setup, calibration and data correction concepts as well as first results from application at the Passaúna reservoir where we focus on turbidity and the water surface temperature.

2. MATERIAL AND METHODS

Assembling of the sensor system is presented in Section 2.1, followed by the radiometric calibration of the sensors which is briefly introduced in Section 2.2. The methods leading to our first results are then presented in Section 2.3.

2.1. Sensor System

The multi sensor imaging system consists of a hyperspectral camera, a thermal camera and a standard RGB camera (see Table 1). To estimate the water quality parameters like turbidity and chlorophyll-a (chl-a) we choose the S185

Figure 1: The sensor system is mounted on a coaxial octocopter. The cameras are stabilised by a two axis brushless gimbal.

Table 1: Sensor specifications as given by the manufacturers.

	S185	Qmini	Tau 2
Wavelength [µm]	0.450 - 0.95	0.225 - 1.0	7.5 - 18.5
Channels	125	2500	1
Resolution [nm]	8 @ 532	1.5	-
Sampling [nm]	4	0.31	-
Weight [g]	490	60	100
Sensorsize	50x50	1	640x512
PAN [Pixel]	1000x1000	-	-
FOV [deg]	33x33	180*	45x37

*cosine corrector

hyperspectral camera from Cubert GmbH with 125 channels in the wavelength range from 450 nm to 950 nm. The camera features snapshot acquisition mode with an additional high resolution panchromatic channel, which can be used for glint identification. We use an upward looking spectrometer with 2500 channels in the range from 225 nm to 1000 nm to calculate reflectance spectra as the ratio between the water leaving radiance, captured by the hyperspectral camera and the downwelling irradiance at the UAV measured by the spectrometer. We use this setup to precisely estimate reflectance spectra, even in conditions with permanently changing cloud cover as it occurs often in southern Brazil. The thermal infrared camera Tau 2 from FLIR is used to measure the temperature of the water surface. For more visual information about the conditions during the flight and for post processing purposes we use the high resolution Survey2 RGB camera from MAPIR. To ensure a synchronous acquisition, the sensors are triggered by one hardware trigger. The sensors are mounted on a two axis gimbal on a coaxial octocopter with $4.5\,\mathrm{kg}$ maximum payload (see Figure 1). For precise navigation which is obligatory for mosaicking we use an RTK GNSS system with a mobile base station. Using the full sensor system and inflatable rescue devices the flight time is around $15\,\mathrm{min}$ including take-off and landing. This equals a mapping area with the S185 camera of $0.1\,\mathrm{km}^2$ at a flight height of $120\,\mathrm{m}$ above ground level.

2.2. Radiometric Calibration

Calculating spectral reflectance as the ratio of radiance measured by different sensors often leads to problems due to unknown sensor characteristics. Without knowing their individual system function, hardware specific bias of radiance measurements causes erroneous parameter estimates. Therefore a proper radiometric cross calibration of the sensor system is essential. In case of using a hyperspectral camera, a cross calibration between the spectrometer and each pixel of the camera becomes necessary. The data captured with our hyperspectral camera shows a strong light fall off to the image margins of each channel and diagonal and concentric circle patterns. These effects can be reduced by first applying a wavelength calibration and second a flatfielding calibration to every pixel of the hyperspectral image [5, 6]. A low cost wavelength calibration can be done by using an off-the-shelf fluorescent lamp. The absolute calibration of the sensors must be done with professional light sources but a low cost relative calibration is also possible using incandescent light and a target with known reflectance properties.

2.3. Data Processing

The estimation of water quality parameters like turbidity is carried out by the processing of water leaving reflectance measurements using the hyperspectral camera. The water leaving reflectance can either be calculated using a white reference or another spectrometer for irradiance measurements. The water quality parameters can be estimated using different methods like band ratios or machine learning approaches [4, 7]. The results presented in this paper are the output of a partial least squares regression (PLS) adapted from [8].

Total reflection of the sunlight at the water surface, also called glint, appears as a random pattern on undulated water surfaces, at points where the surface normal equals the bisecting line between the sun pointing vector and the camera line of sight. These glint biased hyperspectral pixels can be detected by using the simultaneously acquired panchromatic image. This is done for each image by a threshold operation using the high-resolution image to generate a mask for the low-resolution hyperspectral cube. At the current stage we estimate the threshold by visual detection of bright pixels in the panchromatic high resolution image of the hyperspectral camera.

The temperature of the water is also an important parameter to get information about the actual state of a water body. Using thermal cameras on UAV gives the possibility of mapping the surface temperature of water bodies and to make water mixing processes visible. Combined with additional information e.g. weather and bathymetry it is possible to model the temperature distribution in a reservoir. One application of this data is the revealing of illegal sewage water inflows. Further, the correlation between water temperature and algae concentration could be used to enhance the parameter estimation using the hyperspectral data [9].

Due to missing homologous points on the water surface between single captured images, the geocoding of the data

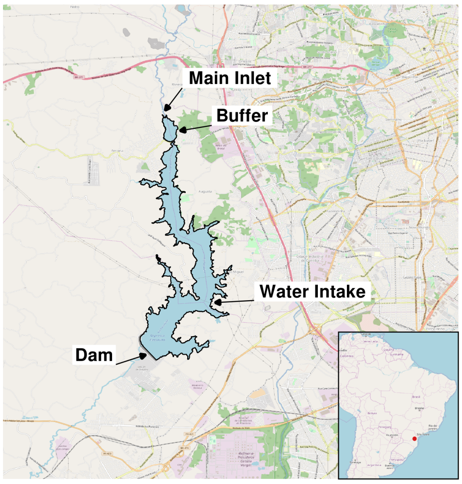


Figure 2: Passaúna reservoir, located in the west of Curitiba, Brazil. Map data ©OpenStreetMap contributors.

is not straight forward and requires a more precise navigation of the drone. In this study we used a RTK GNSS and a gimbal stabilised sensor system to deal with this drawback. The water surface is assumed to be flat and spatial uncertainties of up to $2\,\mathrm{m}$ are passable for mapping of water quality parameters.

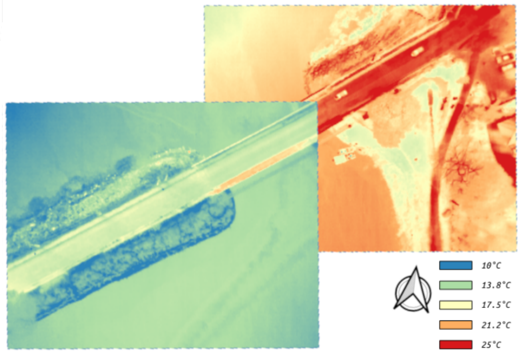
3. FIRST RESULTS – PASSAÚNA RESERVOIR

In this paper we present the first results of two field campaigns at the Passaúna reservoir, located in the west of Curitiba, State of Paraná, Brazil (see Figure 2). The shallow artificial reservoir Passaúna has a water surface of about $9\,\mathrm{km}^2$ and a mean depth of $6.5\,\mathrm{m}$ [10]. The main inflow is in the northern part of the reservoir where the water enters a so called buffer area, which has the basic idea, that sediments can settle down before the water enters the main reservoir. This buffer area and the adjacent northern part of the main reservoir is the most interesting area of the drinking water reservoir. It shows a significant lateral gradient in turbidity, considerable flow dynamics and large temporal variation caused by changing inflow conditions. Therefore the investigations presented in this paper focus on this area.

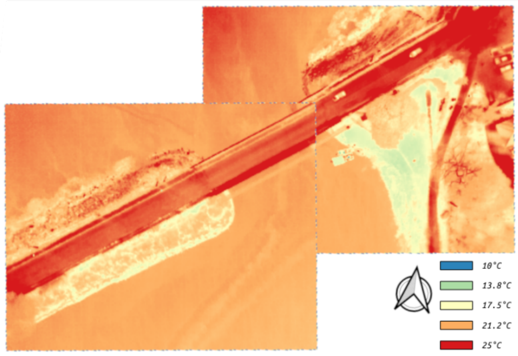
3.1. Data Acquisition

During two field campaigns in February and August 2018, we acquired data with the sensor system presented in Section 2.1. We have remote sensing data of visible RGB, thermal infrared and hyperspectral VIS-NIR images for water quality parameter estimation. At the same time in-situ measurements where carried out and water samples where taken and analysed in the lab. These form the ground truth dataset for training and validation of the water quality estimation algorithms.

During our first experiments we used a stop and go flight mode to capture single images without motion blur. However this caused unacceptable errors of the mosaicking of the images due to too slow gimbal reaction. Therefore we optimised our flight plans and now we use a continuous velocity setting for each flight. With this setup the mosaicking



(a) Unprocessed thermal images.



(b) Drift and vignette corrected.

Figure 3: Radiometric correction of thermal images before (a) and after (b) drift compensation.

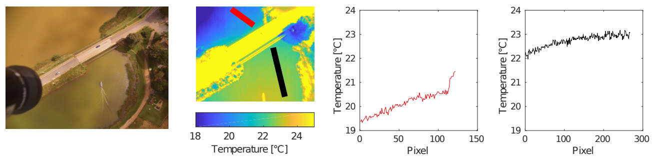


Figure 4: Temperature gradient at the buffer-reservoir link. Figures on the left show the RGB and thermal infrared image. The plots show the surface temperature along the two profiles.

errors are significantly reduced and more than one minute of flight time can be saved. Investigations of the spectral data from a test site with motion blur showed no significant changes in comparison to unblurred data.

3.2. Water Surface Temperature

The thermal infrared images showed vignetting in each frame and a drift from one frame to the next during a flight in winter as shown in Figure 3(a). This figure shows two overlapping images one captured at the beginning of the flight and one $10\,\mathrm{min}$ later, where one would expect only insignificant changes of the surface temperature. Analysis of the metadata of each captured frame show a sensor temperature drift of about $7\,^\circ\mathrm{C}$ during the flight, which equals the offset between the overlapping images. Using the software ThermoViewer and further processing we were able to estimate a mean vignette to correct each frame. After the vignetting correction and the temperature drift compensation the frames perfectly fit to each other. Only a remaining co-registration error due to uncertainties in navigation and geometrical calibration are left.

Another image captured at the same location in summer

ISBN: 978-85-17-00097-3

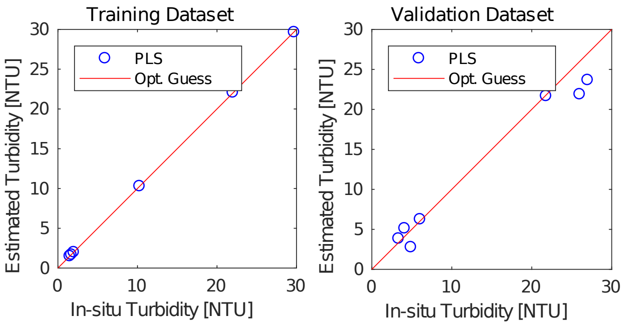


Figure 5: PLS training and validation results for turbidity estimation using four coefficients.

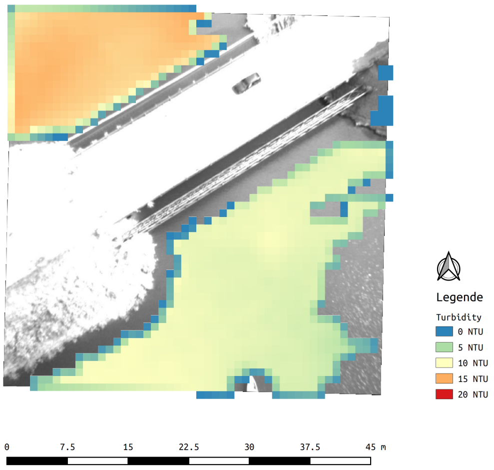


Figure 6: Turbidity gradient at the buffer-reservoir link. The panchromatic grey image of the hyperspectral camera is superimposed by turbidity estimates.

shows a strong gradient between the buffer area and the reservoir (see Figure 4). The profiles show an increase of the temperature from about 20 °C to more than 22 °C in this scene. This confirms the assumption that the colder water of the buffer submerges immediately under the warmer water of the reservoir at the buffer-reservoir link.

3.3. Turbidity Estimation

The turbidity estimation is done using a partial least squares regression (PLS) using absolute spectra, not reflectance spectra. To estimate the coefficients we used spectra with corresponding ground truth data. Figure 5 shows the results of training and validation of the PLS with four coefficients. We achieved a mean relative error of 8 % which is an acceptable result.

The turbidity estimation of the area around the passage from the buffer to the main reservoir is shown in Figure 6. The northward facing panchromatic grey image is superimposed by the false colour visualisation of the turbidity estimation for each hyperspectral pixel of the camera. Clearly visible is the higher turbidity in the buffer and the significant lower values south of the bridge after the water enters the main reservoir. This strong gradient corresponds to the described phenomenon in Section 3.2 and substantiates the above described assumption.

4. CONCLUSION AND FURTHER WORK

In this paper we presented the setup of a lightweight remote sensing system for water quality parameter estimation and first results of two measurement campaigns at Passaúna reservoir. Despite the early stage of evaluation, we achieved promising results which we will improve by optimisation of the hardware and processing setup. In a first step the full integration of the irradiance correcting spectrometer will be implemented for accurate reflectance measurements. To achieve a better mosaicking of the images we will use an enhanced geometric cross calibration of the multi sensor system including the gimbal orientation. Further investigations will focus on an enhanced parameter estimation using machine learning and physical modelling approaches.

5. REFERENCES

[1] LINDSTRÖM, A.; GRANIT, J. *Large-scale water storage in the water, energy and food nexus: Perspectives on benefits, risks and best practices*. Stockholm: Stockholm International Water Institute, 2012.

[2] INTERNATIONAL COMMISION ON LARGE DAMS. *World Register of Dams*. visited at 2018–10–15. Avaliable at: <http://www.icold-cigb.net/GB/world_register/general_synthesis.asp>.

[3] BENGTSSON, L.; HERSCHY, R. W.; FAIRBRIDGE, R. W. (Ed.). *Encyclopedia of lakes and reservoirs*. Dordrecht: Springer, 2012. (Encyclopedia of earth sciences series). ISBN 978-1-4020-5616-1.

[4] GHOLIZADEH, M.; MELESSE, A.; REDDI, L. A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. *Sensors*, v. 16, n. 8, p. 1298, ago. 2016. ISSN 1424-8220.

[5] KERN, J.; SCHENK, A.; HINZ, S. Radiometric calibration of a uav-mounted hyperspectral snapshot camera with focus on uniform spectral sampling. In: *2018 9th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. [S.l.: s.n.], 2018.

[6] AASEN, H. et al. Introduction and preliminary results of a calibration for full-frame hyperspectral cameras to monitor agricultural crops with UAVs. In: *ISPRS Technical Commission VII Mid-Term Symposium 2014*. [S.l.: s.n.], 2014.

[7] MAIER, P. M.; KELLER, S. Machine learning regression on hyperspectral data to estimate multiple water parameters. In: *2018 9th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)*. [S.l.: s.n.], 2018.

[8] WAGNER, A. et al. Proximal vis-nir spectrometry to retrieve substance concentrations in surface waters using partial least squares modelling. *Water Science and Technology: Water Supply*, in review.

[9] MILLER, W.; RANGO, A. Using Heat Capacity Mapping Mission (HCMM) Data to Assess Lake Water Quality. *JAWRA Journal of the American Water Resources Association*, v. 20, n. 4, p. 493–501, ago. 1984. ISSN 1752-1688.

[10] CARNEIRO, C.; KELDERMAN, P.; IRVINE, K. Assessment of phosphorus sediment-water exchange through water and mass budget in Passaúna reservoir (Paraná state, Brazil). *Environmental Earth Sciences*, v. 75, n. 7, apr 2016. ISSN 1866-6280, 1866-6299.