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Modelling of Kuibyshev reservoir shallow water depths by bathymetric surveys and multispectral UAV imagery data: a case study

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Abstract. This study investigates the potential of using multispectral Unmanned Aerial Vehicle (UAV) imagery to model the shallow water depths of the Kuibyshev Reservoir, Russia. Traditional methods like boom soundings and echo sounders, while accurate, are labor-intensive and costly. By leveraging multispectral data from UAVs, we aim to provide a more efficient and detailed approach to bathymetric mapping. Our methodology involved conducting bathymetric surveys with a Garmin GPS Map 178C and a Geoscan 401 Geodesy UAV equipped with a MicaSense RedEdge-MX camera. We performed correlation analysis and modelled depth using various regression techniques, identifying the Decision Tree Regressor as the top-performing model with an R^2 value of 0.98. Our findings suggest that UAV multispectral bathymetry is a viable alternative for local-scale shallow water mapping, with significant implications for reservoir management and ecological studies.

1 Introduction

Water depth data is crucial for the effective management of aquatic lands. Traditional methods of measuring water depth, such as boom soundings, echo sounders and side-scan sonars, are highly accurate [1]. However, the labour-intensive nature of field surveys, the need for repeated surveys and the high cost of measurements makes it essential to identify more efficient methods of studying underwater topography.

Since the advent of satellite remote sensing technology, there has been a continued effort to estimate the depth of waters. As the number of satellite sensor types increases, there is a growing availability of underwater terrain modelling capabilities [2]. Active sensors, such as light detection and ranging (LIDAR) systems [3], and passive sensors (multi- or hyperspectral) are used to comprehensively acquire shallow-water bathymetry data over large-scale areas. The scientific literature contains a number of methods that utilise the visible optical range [4-5], multispectral [6] and hyperspectral [7] data.Approaches used for bathymetry modelling include Artificial Neural Network (ANN) [8], linear regression, Bierwirth algorithm, Random Forest [9], cluster-based regression (CBR) algorithm [10] and spectral differential statistical methods. Optical sensors have been successfully employed for the mapping of relatively shallow waters in areas with

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sufficient water clarity [11]. The quality of bottom map production depends on the type of images used. Surveys using multispectral images show better quality because they allow additional image channels to be used to classify bottom types, leading to improved results [12].

UAV multispectral bathymetry may be a suitable alternative to satellite data for creating bathymetric maps of shallow water in local areas [13]. The technology of multispectral UAVs, with their enhanced spatial resolution, offers the potential to rapidly generate more detailed maps, as well as to plan and adapt the parameters of multispectral data acquisition to survey conditions [14]. To build depth models, the comparison of index values calculated from multispectral data with measured depth values is used. Once the data has been verified, the obtained dependencies are extrapolated to unvisited territories.

The majority of scientific research devoted to determining the depth of water reservoirs is devoted to the study of marine areas. This is due to the high transparency of water and good visibility of the bottom of the sea. In reservoirs, the situation is more complicated and the visibility of the bottom is determined by the rocks that form the reservoir bed, the force of currents and wind waves, as well as the fluctuation of the water level in regulated reservoirs. Therefore, most of the research is devoted to water level determination and reservoir capacity estimation [15]. Remote sensing offers many possibilities for determining the water depth in water reservoirs, but most of the studies make use of satellite radar altimetry to measure the water depth [16, 17]. Nevertheless, the study of the topography of the shallow part of reservoirs is an important task, given the great importance as a source for fresh water and sustain activities such as agriculture, fisheries and recreation, and large impact on the hydrology and the ecology of the surrounding environment.

This study presents work on shallow water depth determination of the Kuibyshev Reservoir (Russia) as part of the work of the water site of the Carbon Volga polygon. A study of the shallow waters of the Kuibyshev Reservoir was conducted within the Saralinskiy section of the Volga-Kama State Biosphere Reserve. The site is bounded from the north by the shoreline and from the south by a semi-round elongated island, which represents a remnant of the ridge elevations of the drowned floodplain of the Volga River.

2 Materials and Methods

To provide a comprehensive description of the underwater topography of the study area, bathymetric surveys were conducted on a Flagship PVC boat utilising a Garmin GPS Map 178C chartplotter with depth coordinate referencing in the WGS 84 system (Figure 1, a). The multispectral survey was conducted using the Geoscan 401 Geodesy UAV (Figure 1, b) with a MicaSense RedEdge-MX multispectral camera (RX02 series) (Figure 1, c).

Fig. 1. Equipment used in the field surveys. Boat with Garmin GPS Map 178C chartplotter (a), Geoscan 401 Geodesy UAV (b), MicaSense RedEdge-MX camera (c).

Resulted dataset, stored in a CSV file, included multiple indices such as NDVI, GNDVI, SAVI, RENDVI, CIre, CIgreen, PRI, MSAVI, TDVI, NDWI, TCAVI, GREEN, and RED, with corresponding depth measurements in meters (Figure 2).

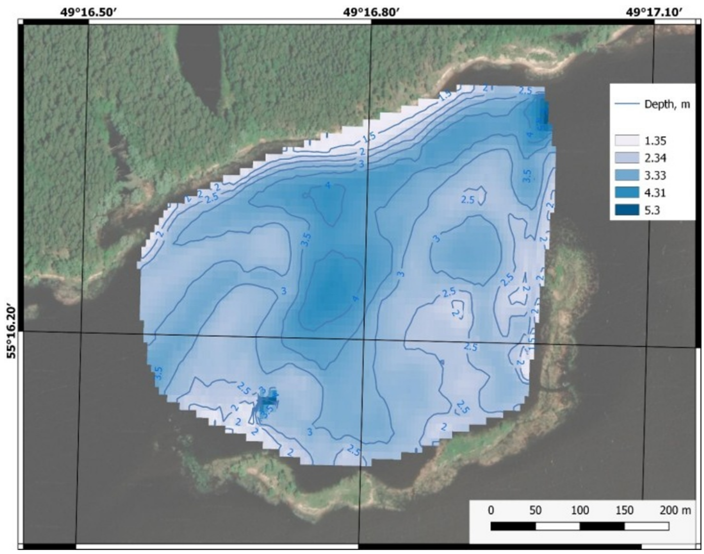

Fig. 2. Bathymetry map of the shallow water test area.

Initial data preprocessing involved loading the dataset into a pandas DataFrame and performing data cleaning to remove any missing values. Subsequently, a correlation analysis was conducted to determine the relationship between the indices and depth measurements. This analysis involved computing the correlation matrix and visualizing it using a heatmap. Predictors with an absolute correlation coefficient greater than 0.3 were selected for further analysis (Figure 3).

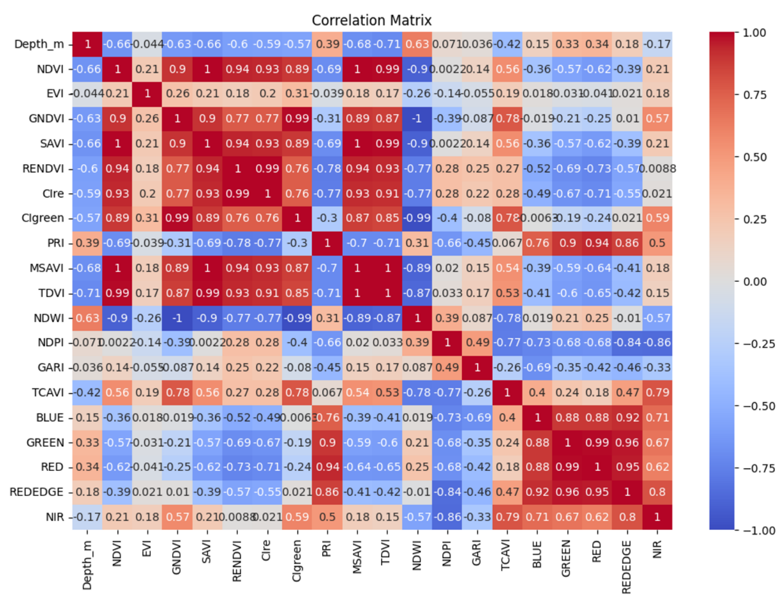

Fig.3. Correlation matrix of model predictors.

To explore the relationship between the selected predictors and depth, scatter plots were generated for each predictor against depth (Figure 2). The predictors demonstrating significant correlations were then used to create all possible combinations for model training. The selected models included Linear Regression, Ridge Regression, Lasso Regression, Elastic Net, Random Forest, Decision Tree, and Gradient Boosting. Each model was trained and evaluated using the sklearn library. The dataset was split into training and testing sets using a 70:30 ratio, ensuring a robust evaluation framework. For each combination of predictors, models were trained on the training set and evaluated on the testing set. The performance metrics included mean squared error (MSE) and R-squared (R^2) values.

Parallel processing techniques were employed to expedite the model training process. The joblib library facilitated efficient parallelization of the computations. The best performing models for each type were identified based on the highest R^2 values. Visualization of the results included bar plots for R^2 and MSE, as well as scatter plots for observed versus predicted values for the best model. This comprehensive approach ensured a detailed understanding of the predictive capabilities of various indices in estimating water depth.

3 Results

The correlation analysis revealed significant relationships between several indices and depth measurements. Notably, indices such as NDVI, GNDVI, SAVI, MSAVI, and TDVI exhibited strong negative correlations with depth, while NDWI and GREEN showed positive correlations. The scatter plots illustrated clear trends, with certain indices displaying linear relationships with depth, validating their potential as reliable predictors (Figure 4).

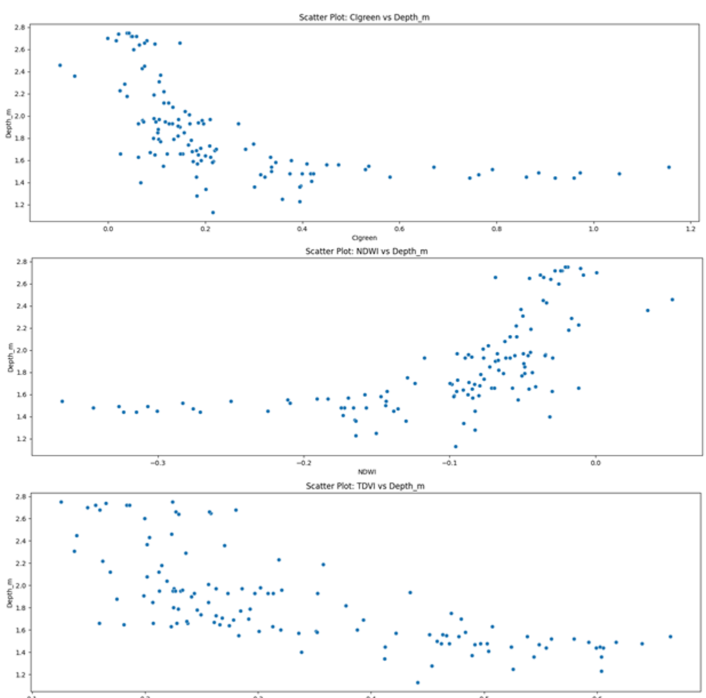

Fig.4. Scatter plots for CIgreen, NDWI, TDVI indices and shallow water depth values.

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Modelling results highlighted the Decision Tree Regressor as the top performer, achieving an R^2 value of 0.98 and an MSE of 0.002 when utilizing the combination of TCAVI, GREEN, and RED indices. Gradient Boosting also demonstrated robust performance with an R^2 of 0.89 and an MSE of 0.019 using the same predictor set. Conversely, Elastic Net Regression, although included in the analysis, yielded comparatively lower R^2 values, indicating limited predictive power for depth estimation in this context. The comprehensive evaluation of all possible predictor combinations across multiple regression models underscored the importance of model selection and predictor combination in optimizing predictive accuracy.

Visualizations of the results provided further insights. Bar plots for R^2 (Figure 5) and MSE values clearly delineated the superior performance of tree-based models compared to linear models. Additionally, scatter plots of observed versus predicted values for the best-performing model (Decision Tree) illustrated an almost perfect alignment, affirming the model's efficacy. Residual analysis confirmed the robustness of the model, with residuals displaying minimal deviation from zero, indicating high predictive reliability.

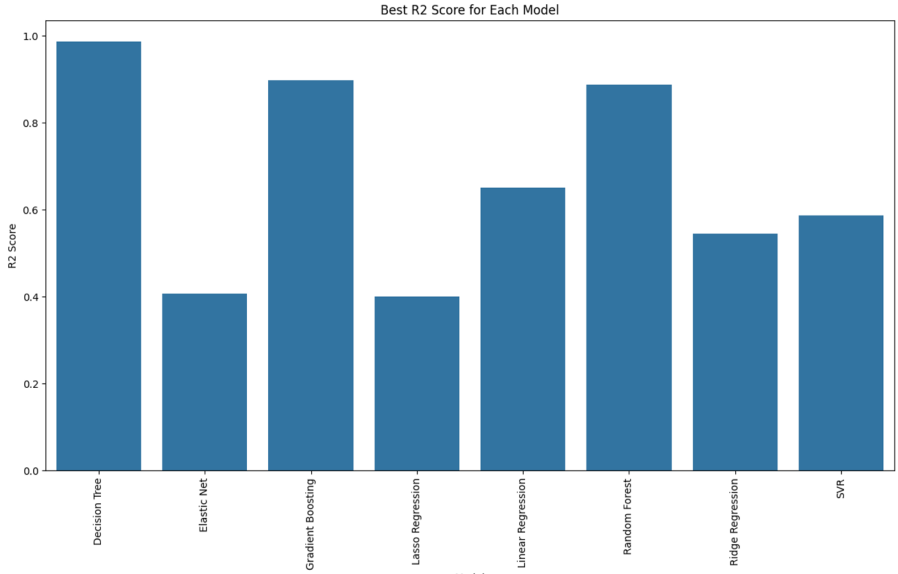

Fig. 5. Quality assessment of different machine learning models for different combinations of predictors (best fits for each model).

Additional analysis was performed for more detailed analysis and selection of the resulting model. Since at the previous stage the model based on Decision Tree Regressor seemed to be the most promising in terms of statistical metrics, it was chosen as the main model. However, since dividing the sample into training and validation samples in the ratio of 80/20 led, as it seems to us, to overtraining of the model, the sample was divided in the ratio of 70/30. In this form, the R2 value of the validation sample was 0.89 and the mean absolute error was 7 cm. Nevertheless, it is evident from the error plot and scatter plot that the predictive ability of the model in shallow waters deeper than 2 m becomes unstable. This appears to be due to the decreasing penetration of light in different ranges of the spectrum with increasing depth (Figures 6 and 7).

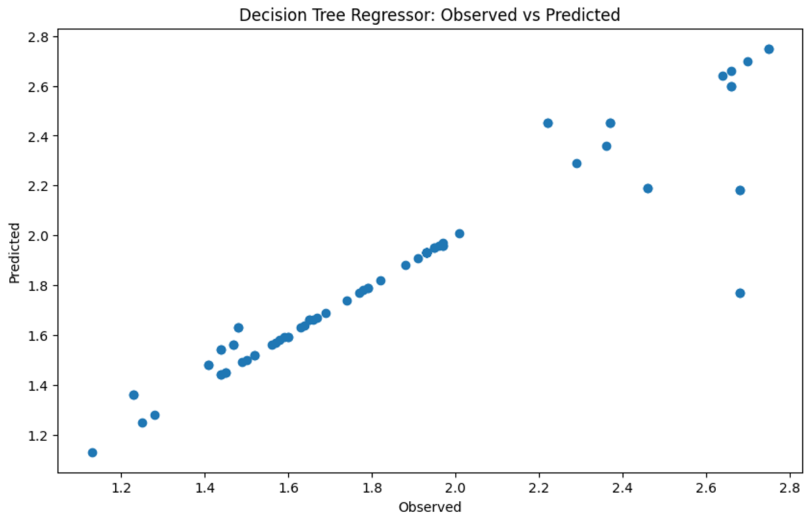

Fig. 6. Scatter plot of observed and predicted values for Decision Tree Regressor model.

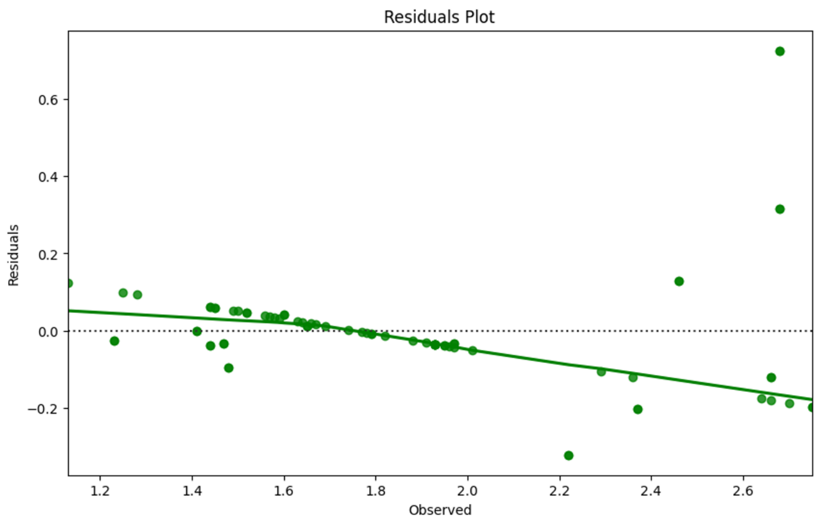

Fig. 7. Residuals plot of observed and predicted values for Decision Tree Regressor model.

Thus, the depth of shallow waters determines the scope of application of multispectral UAV imagery. For such works it is advisable to use space imagery having bands with longer wavelengths with greater penetrating power.

4 Conclusion

The use of multispectral UAV imagery for modelling shallow water depths in the Kuibyshev Reservoir has demonstrated promising results. Our study showed that UAVs equipped with advanced multispectral cameras could efficiently gather high-resolution data, providing a cost-effective and less labor-intensive alternative to traditional bathymetric survey methods. The Decision Tree Regressor emerged as the most accurate model for predicting water depths, with an R^2 value of 0.98, underscoring the potential of tree-based models in handling complex, non-linear relationships in environmental data.

The significant correlations found between various spectral indices and water depth validate the utility of remote sensing in bathymetric studies. Specifically, indices such as NDVI, GNDVI, SAVI, MSAVI, and TDVI demonstrated strong negative correlations with depth, while NDWI and GREEN exhibited positive correlations. These findings highlight the importance of selecting appropriate spectral indices to enhance the accuracy of depth predictions.

Despite the successful application of multispectral UAV imagery in this study, some limitations were observed. The model's predictive ability decreased for depths greater than 2 meters, likely due to reduced light penetration at greater depths. This limitation suggests that for deeper water bodies, integrating multispectral UAV data with longer wavelength satellite imagery could improve accuracy.

Future research should focus on refining these models by incorporating additional environmental variables and exploring the integration of different remote sensing technologies. Expanding the study to include various types of water bodies with differing turbidity and bottom compositions could also provide a more comprehensive understanding of the capabilities and limitations of UAV-based bathymetric mapping.

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