Machine Learning for Long-Term Riparian Vegetation Monitoring Using Historical Aerial Imagery

Apprentissage automatique pour le suivi à long terme de la végétation riveraine à l'aide d'images aériennes historiques

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RÉSUMÉ

Les photographies aériennes historiques sont généralement considérées comme une source fiable d'informations sur l'évolution passée de l'occupation et de l'utilisation des sols. Cependant, l'extraction d'informations à partir de ces données peut être complexe en raison des informations spectrales limitées des images en noir et blanc. Cette étude évalue une approche basée sur les textures qui utilise des modèles d'apprentissage automatique pour identifier les motifs spatio-temporels du système multicanal à chenaux divagants dans des images aériennes historiques, avec une attention particulière à la végétation riveraine. Nous avons utilisé les méthodes d'apprentissage automatique Random Forest (RF), Light Gradient Boosting Machines (LightGBM) et Extreme Gradient Boosting (XGBoost) à travers deux schémas de classification pour classer cinq jeux de données aériennes (1949-1992) en cinq classes principales. Les résultats ont montré l'efficacité des opérations morphologiques (gradient, érosion, et dilatation) et des caractéristiques GLCM (contraste, entropie) dans les cartes classifiées finales. Le modèle RF a démontré une plus grande stabilité et une précision médiane plus élevée sur l'ensemble des jeux de données, tandis que les performances de XGBoost étaient notablement plus variables mais considérablement plus rapides. Malgré les défis et les limitations, l'approche appliquée dans cette étude peut améliorer le suivi des changements de la végétation riveraine au fil du temps, notamment en utilisant des images aériennes historiques en noir et blanc.

ABSTRACT

Historical aerial photographs are commonly known as a reliable source of information on past land cover and land use. However, extracting information from such data can be challenging due to the limited spectral information in black-and-white images. This study assesses a texture-based approach that employs Machine Learning models to identify the spatial-temporal patterns of the braided-wandering multichannel system in historical aerial images, with a particular focus on riparian vegetation. We used Random Forest (RF), Light gradient boosting machines (LightGBM), and Extreme Gradient Boosting (XGBoost) Machine Learning methods through two classification schemes to classify five aerial datasets (1949 -1992) images into five main classes. The results indicated the efficacy of Morphological operations (Gradient, Eroded, and Dilated) and GLCM features (contrast, entropy) in the final classified map. The RF model demonstrated greater stability and higher median accuracy across datasets, whereas XGBoost's performance was notably more variable but significantly faster. Despite the challenges and limitations, the approach applied in this study can enhance the monitoring of riparian vegetation changes over time, especially when utilizing historical black-and-white aerial imagery.

KEYWORDS

Aerial orthophotos, machine learning, riparian vegetation, textural and morphological features, Random Forest

Orthophotos aériennes, apprentissage automatique, végétation riveraine, caractéristiques texturales et morphologiques, Random Forest

1 INTRODUCTION

Historical aerial images are invaluable tools for monitoring planimetric changes and documented spatial river adjustment, floodplain evolution or vegetation succession (Rusnák et al., 2016). The historical archive of aerial images enables the identification of past events and processes or diachronic analyses. However, although BW aerial photographs usually have a relatively high spatial resolution, they lack spectral information (Tsai et al., 2005), and object detection is based on single panchromatic histogram analyses.

A new technology development enables improved image analysis by using a "big data" approach with the application of artificial intelligence (AI) to detect objects, assess them, and understand the river system. Nonetheless, the application of historical aerial images is still laid on visual and manual vectorization. Especially for automatic processing of black-and-white aerial images with lower quality and spectral resolution the importance of the texture is acknowledged. A combination of the performance of machine learning models with textural information (such as GLCM textural properties, and morphological features) is beneficial for object delineation from high-resolution B&W time series of historical images. Automatic classification of the riparian zones and riverine landscape has been experiencing significant growth by focusing on the present RGB and multispectral images from satellites or drones (P. E. Carbonneau & Bizzi, 2023).

Many studies demonstrated superior classification accuracy when utilizing GLCM textural features along with spectral properties of multi-spectral satellite images and multi-spectral aerial images. Although few studies have investigated the impact of using textural properties for historical aerial image classification.

However, advancements in machine learning, particularly when combined with textural analysis, offer promising solutions for monitoring past event in riparian landscape. The ML models can enhance the classification and delineation of objects in B&W images. In this study, our main objective is to detect the spatial pattern of the braided-wandering multichannel system from historical aerial images with an emphasis on vegetation. Moreover, we explore the potential of different textural metrics to enhance classification results by applying three commonly used classification algorithms, Random Forest, Light GBM and Xboost, and solve the research gap by looking at how can old aerial images be assessed for automatic channel transformation analyses.

2 METHODOLOGY

Historical B&W aerial photographs from 1949 – 1992 with very high resolution (up to 0.5 m) were used for the extraction of vegetation cover extent in the riparian zone of the Belá River. Various textural and geomorphological features were extraxted from single band images. For final classification three models: Random Forest, LightGBM and XGboost Machine Learning models were applied and tested in terms of their feasibility of classification after individually optimising their different parameters. All the algorithms were implemented using open-source Python libraries.

In the study area, an intensive manual on-screen annotation procedure was applied for all high-resolution orthophotos and manually labelled datasets were divided into two independent parts : one for model training and testing, and one for validation procedure. In the riparian zone, six main classes : i) artificial surface, ii) cropland, iii) water, iv) bare-land and gravel bars, v) grass-land, and vi) forest were manually identified and labeled for all datasets. We used GLCM textural properties, and morphological features to extract and select diverse features from normalised and pre-processed B&W images. Three machine learning methods through two classification schemes were used for classification : RF, LightGBM, and XGboost. For optimization, the final model was tuned through detailed analysis of the input parameters for each individual model separately. Fivefold cross-validation was used to evaluate the performance of a machine learning model. Each model was trained on 75% of reference data, and the remaining 25% was utilized for testing or evaluating model performances. Sequential Feature Selection (SFS) was used to select the optimal feature subset of the dataset for classification. The procedure involved adding features incrementally until the accuracy began to increase significantly, with each additional feature indicating relatively high accuracy and low computational costs could be achieved with a reduced data volume (Zhang et al., 2021).

For classification, two classification schemes were defined. The first was applied on all 15 features which were extracted from B&W images (A), and the SFS results of feature selection were considered for the second scheme (B). The accuracy assessment metrics were derived from the confusion matrix and conducted for each classified map separately using validation reference samples. Finally, from the best-performed classification model (RF), we selected only vegetation class for each study period to analyse the vegetatioin dynamics in the study area. Spatiotemporal changes between two consecutive time horizons were detected in stable areas where vegetation cover is present for both years and increase (afforestation) and decrease of vegetation cover (deforestation). Longitudinal changes were analysed for 500m-long river reaches that were numbered in the upstream direction. Finaly, statistical analyses was performed in RStudio.

3 RESULT

Feature importance analysis showed that gradient, eroded, and dilated features are the most critical across all models, with RF and LightGBM prioritizing these features over GLCM features. The RF model outperformed others with the highest accuracy (90%) and F1-score (89%) while maintaining consistent performance across datasets, though LightGBM and XGBoost showed competitive but more variable results, particularly in earlier datasets. The Sequential Feature Selection (SFS) process identified an optimal feature set for each model, with seven features consistently selected across all models. Classification results from Scheme B showed comparable or slightly improved overall accuracy (OA) and F1-scores relative to Scheme A, while significantly reducing runtime for all models—most notably improving XGBoost's efficiency and accuracy. Vegetation dynamics in the floodplain from 1949 to 1992 were analyzed using RF classification results, showing a gradual increase in vegetation cover from 310 to 597 hectares, with the most significant growth occurring between 1961 and 1986. Continuous afforestation and stable forests contributed to this increase, particularly in the period 1986–1992, where forested areas expanded from 205 to 521 hectares.

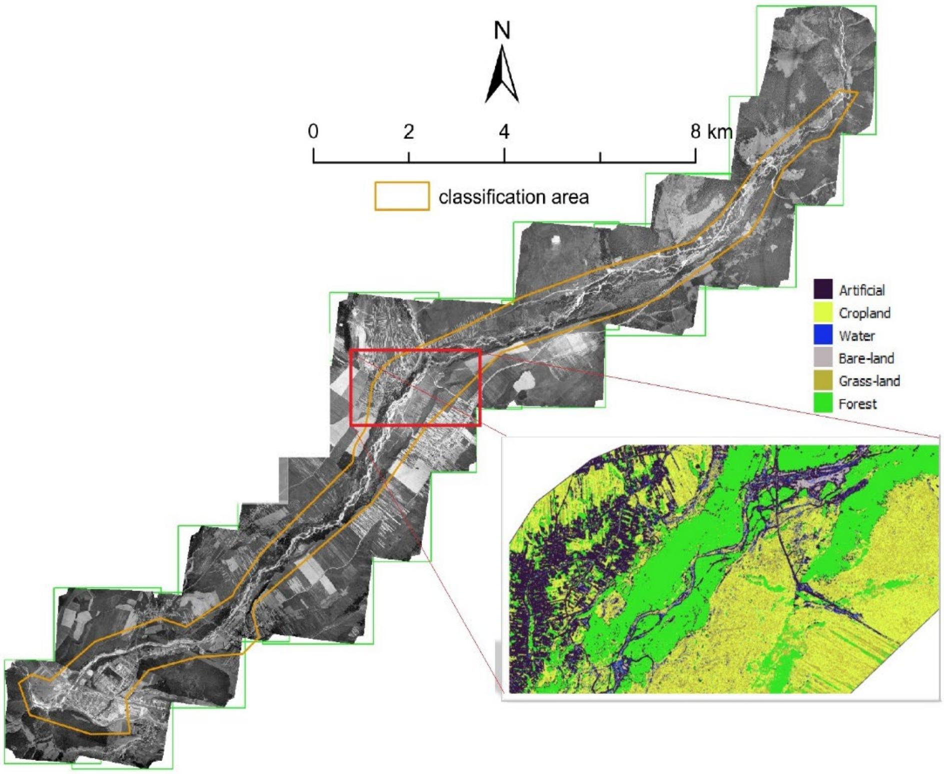

Figure 1. RF classification result for the year 1973.

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