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A deep-learning model for predicting the planform evolution of braided sand-bed rivers

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Introduction

Braided rivers are the most dynamic type of rivers, with a rapid and intricate morphological evolution (*Stecca et al.*, 2019). Being able to predict where and how rivers evolve is crucial for supporting spatial-related decision-making processes in the vicinity of these rivers. However, a limited understanding and inadequate algorithm implementation of specific morphological processes limits the prediction capabilities of physics-based models (*Jagers*, 2003; *Siviglia and Crosato*, 2016). The design of structures, infrastructure, and other interventions is consequently hampered at the expenses of the popoulation safety. In recent years artificial intelligence techniques rapidly gained popularity across different contexts (*Blake et al.*, 2021) and the availability of satellite images increased. This research sets a novel attempt to predict the planform evolution of braided rivers by means of a deep-learning algorithm and using satellite images. The Brahmaputra-Jamuna River, in India and Bangladesh, was selected as case study (*Best et al.*, 2022).

Methods and data

The stretch of river that was considered ranges from the confluence with the Lothi and Dibang River, in India, until the confluence with the Ganges River, in Bangladesh. The training, validation, and testing datasets were obtained by spatially splitting the stretch considered. Thirty rectangular sub-reaches with 60×30 km dimensions were generated, with 60 and 30 km being the longitudinal and lateral dimensions, respectively. The twenty-eight most upstream sub-reaches were used for training the model. The last two reaches were used for validating and testing it, respectively.

A convolutional neural network (CNN) with U-Net architecture was developed (*Ronneberger et al.*, 2015). The model was trained with the Global Surface Water Dataset (GSWD) (*Pekel et al.*, 2016), which contains pre-classified global images with three classes: *no data*, *non-water*, and *water*. An algorithm was implemented to binarize the images by replacing the *no data* pixels with one of the two other classes. The model was trained for a binary semantic segmentation task, aiming at classifying each pixel as either *non-water* or *water*. Four images, representative of the same month over four consecutive years, were used as inputs. The fifth-year image represented the target.

Results

The model demonstrated acceptable skills in predicting the overall planform development, although it often misses finer details and some morphological features (Fig. 1). Processes like the migration of meanders, the abandonment of channels, and the evolution of confluences and bifurcations were often well captured (Fig. 2).

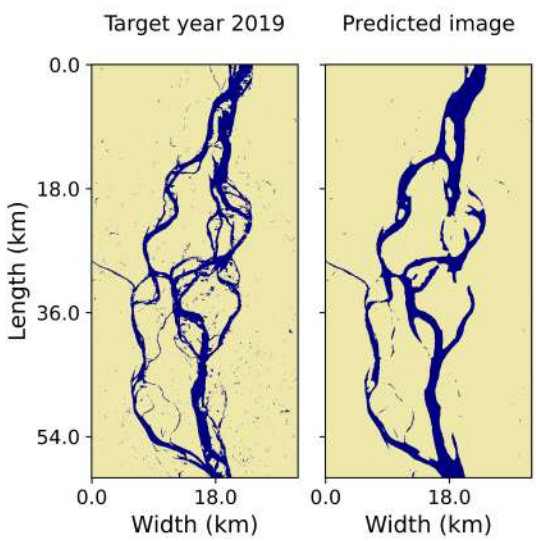

Figure 1: Example of a target and predicted image (year 2019).

However, a lack of temporal patterns was noticed. More complex phenomena, like the formation and shifting of channels, were never predicted, and the total areas of erosion and deposition were constantly underpredicted.

Metrics such as precision, recall, F1-score, and critical success index (CSI) were tracked.

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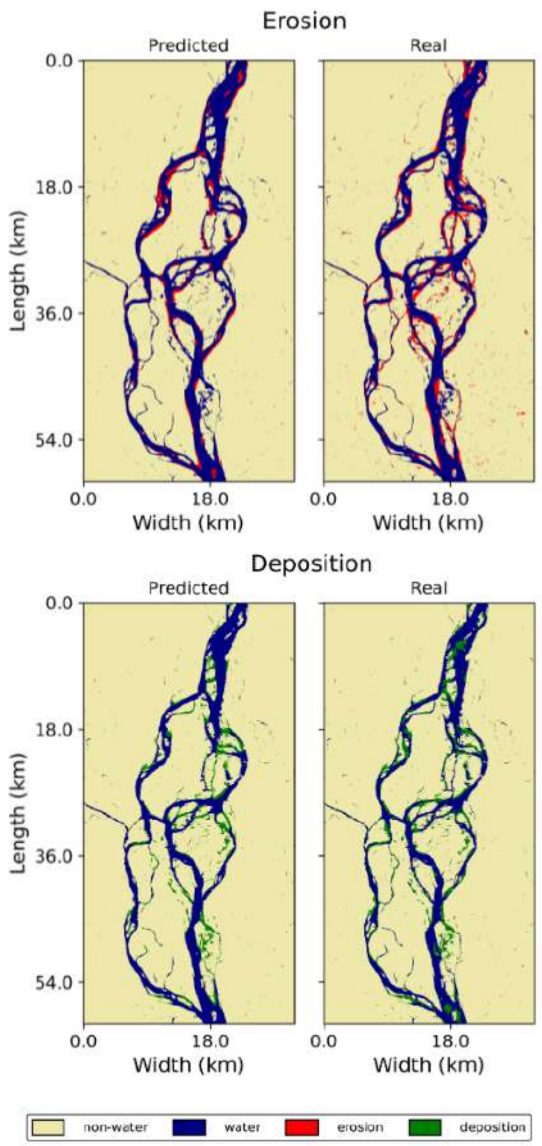

Figure 2: Predicted and real areas of erosion and deposition (year 2019).

These scores show the overall good prediction skills of the model, although larger values are always preferred. A 5-6% total improvement of these metrics was achieved compared to the benchmark method for which no morphological change is assumed to occur (Tab. 1). Additional metrics, like the Receiver Characteristic Operating (ROC) and the Precision-Recall (PR) curves, also show the model ability to accurately predict the *non-water* pixels, whereas struggling more when predicting *water* pixels.

Table 1: Comparison between the metrics of our model and the no-change method benchmark.

Model	Precision	Recall	F1	CSI
Our model	0.72	0.71	0.71	0.55
No-change	0.66	0.66	0.66	0.49

Conclusion and recommendations

Our model could be useful as a preliminary tool for water management authorities in India and Bangladesh. It could support the prioritisation of bank protection measures in areas subject to erosion or land reclamation projects in areas subject to deposition and assist inland navigation. However, given the inherent tendency of the model to underpredict erosion, caution is always advised.

More research is required to improve the current model. Despite this, deep-learning modelling could become a potentially valuable field of research. Testing alternative model architectures, increasing the datasets size, and incorporating additional data, such as water levels or river discharge, are recommended to improve the model performance.

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The code repository is available on GitHub at the following link: https://github.com/antoniomagherini/jamunet-morpho-braided.

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