Evaluation of neural network on sediment transport

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1.0 Research purpose

Increased human activities driven by rapid industrialization have significantly contributed to elevated levels of sediment entering stream systems. These activities, including agriculture, construction, industry, and wasteland management, accelerate soil erosion and disrupt the natural land cover, consequently amplifying sediment runoff into watercourses. Excessive sedimentation, as a result of increased sediment transport, may have detrimental effects on disaster prevention and ecosystem protection in river systems. Furthermore, excessive sedimentation can lead to alterations in coastal and beach morphology, causing damage to infrastructure and eroding cultural heritage sites. As a result, the quantification of a river's sediment transport capacity has garnered significant attention from researchers globally. However, the accurate prediction of sediment transport remains a challenging research topic, making it a research topic of interest.

Several equations have been proposed to estimate sediment transport, including the alongshore transport equation. However, these equations may not be reliable for estimating sediment transport under various conditions, such as during storms. Consequently, measured hydrodynamics are necessary to reduce the bias in the obtained results. In addition, several sediment transport functions have been applied based on various concepts and approaches to enhance the accuracy of sediment transport estimations. However, due to the inconsistency in the obtained results, these approaches have yet to achieve universal acceptance. Kitsikoudis et al. employed three machine learning techniques to derive sediment transport formulas for sand-bed rivers from field and laboratory flume data (artificial neural networks, symbolic regression based on genetic programming, and an adaptive-network-based fuzzy inference system). They subsequently compared the techniques' efficacy. Their findings indicated that the machine learning techniques outperformed the commonly used sediment transport formulae. Therefore, the application of neural networks (NNAs) holds the potential to identify sedimentation sources in catchment basins accurately. In addition to quantifying the sediment stream capacity, it is imperative to comprehend sediment sources in order to implement effective management strategies that minimise soil erosion, thereby reducing sediment loads in streams.

2.0 Methods

A neural network analysis (NNA) was employed to identify sediment sources within Japan's Oromushi River Catchment Basin, based on geochemical data obtained from X-ray fluorescence (XRF) and X-ray diffraction (XRD) analyses. The Oromushi River Catchment Basin in Hokkaido, Japan, was selected for a study to elucidate suspended sediment (SS) production. The basin, characterised by its predominantly forested landscape with some agricultural areas, was subdivided into 12 land groups with 18 sampling locations. The subdivision of the land groups was based on factors such as land use and vegetation type. X-ray fluorescence (XRF) and X-ray diffraction (XRD) analyses were conducted on soil samples to determine elemental composition and mineralogical composition, respectively. A simplified three-layer neural network analysis (NNA) model was employed to discern sediment sources within the Oromushi River Catchment basin. The model, trained utilising a backpropagation algorithm and modified sigmoid function, was designed to minimise errors between desired and predicted outputs, thereby estimating sediment transportation rates. The X-ray fluorescence (XRF) and X-ray diffraction (XRD) analyses generated datasets that were used as inputs in the NNA model.

3.0 Results

The XRF analysis revealed 15 geochemical components as the main constituents of suspended solids (SS) within the Oromushi River Catchment Basin. Based on the geochemical composition of the soil samples, SiO2, a byproduct of volcanic eruptions, was the dominant SS component in the region. In addition, SiO2 exhibited a consistent trend across all 18 sampling stations. Thus, surface soil type significantly influences sediment generation and transportation within the catchment basin.

To determine the origin of geochemical components, we used a neural network model. The XRF-derived sediment component geochemical composition and peak XRD intensities from all sampling stations were used as input data. We assumed that SS was transported directly from the groups to the downstream area, and therefore, our input layers were directly connected to the middle layers. XRF analysis confirmed agricultural fields as the primary source of SS in the Oromushi River Catchment Basin, supporting Beitia *et al*. (2016) results. However, X-ray diffraction (XRD) results revealed some discrepancies with the XRF results. These discrepancies may be attributed to the distinct characteristics of XRF and XRD. XRD provides more detailed information, including mineral species and phases, while XRF only provides chemical composition. Furthermore, XRD demonstrated superior performance in this study, offering more comprehensive sample characteristics in addition to excluding carbon during the analysis, thereby yielding reliable results. To determine SS contribution from sub-river basins, it is crucial to exclude organic compounds. Therefore, we recommend XRD analysis, particularly for studying the contribution of non-organic matter in SS sediment.

Conclusion

X-ray fluorescence analysis revealed agricultural fields as the primary source of suspended sediment in the Oromushi River Catchment Basin. However, X-ray diffraction analysis indicated that volcanic ash regions exhibited the highest sediment transport rates, underscoring the substantial impact of soil surface cover type on sediment transport.

References

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